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National Institute of Mental Health

Series HN No. 1

Operations Research and the Mental Health Service System

Volume I

Report of Ad Hoc Advisory Group

Series HN No. 1

Operations Research and the Mental Health Service System, Volume 1

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REPORTS

Operations Research and the Mental Health Service System

Volume I
Report of Ad Hoc Advisory Group

Edited by

Larry G. Kessler, Sc.D.
Statistician

U.S. DEPARTMENT OF HEALTH AND HUMAN SERVICES
Public Health Service
Alcohol, Drug Abuse, and Mental Health Administration

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PREFACE

Today's mental health service system is in a state of rapid flux. Changing patterns in the use and financing of mental health services and in the distribution and responsibilities of professional staff are only a few of the important issues confronting the mental health services community at the beginning of the 1980s.

In 1979, the Division of Biometry and Epidemiology, National Institute of Mental Health (NIMH), established a new research grant program in Mental Health Service System Research. As its title implies, the focus of this solicitation is on the system-related aspects of mental health care in the United States. Several disciplines that have been involved in the field of health services research were subsequently encouraged to provide their critical perspectives on the mental health service delivery system.

One discipline that has a considerable level of expertise in both multidisciplinary research and the health services research field is operations research. Thus, on March 6 and 7, 1980, an ad hoc advisory group meeting of health operations researchers and NIMH staff convened in Bethesda, Maryland. Their focus was the potential contributions of operations research to our understanding of the mental health service system.

In preparation for this conference, the Division of Biometry and Epidemiology had prepared an annotated bibliography and critical review of operations research studies of the mental health service system by Jack E. Scott; this is contained in Volume II.

The conference format included the presentation and discussion of commissioned papers on four major topics of interest to NIMH. Each paper sought to discuss the relevant mental health and health operations research literature, as well as to propose areas for future investigation. The four topics included (1) the modeling of need, demand, and utilization of mental health services, (2) mental health program evaluation, (3) resource allocation within the mental health service system, and (4) the modeling of large-scale system interactions.

Volume I includes versions of those papers completed after the discussion of the complexities of the mental health service system. The papers include many of the discussants' comments. The meeting generated a number of worthy ideas that could be used in developing an interface between the fields of operations research and mental health services research. It is hoped that publications of these papers will further stimulate interaction between these fields of research.

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EXECUTIVE SUMMARY

William P. Pierskalla, Ph.D.

I. INTRODUCTION

On March 6 and 7, 1980, the Division of Biometry and Epidemiology, National Institute of Mental Health, in conjunction with the Health Applications Section of the Operations Research Society of America, sponsored a meeting on "Operations Research and the Mental Health Service System." The basic purpose was to bring together a group of leaders in mental health services research and health operations research to develop a coherent and rational set of research priorities in the interface of these areas. Participants made presentations on the major areas in mental health services research (MHSR), assessed the state of our knowledge related to operations research (OR) methodologies and their uses in health services research, and identified promising areas in the future of OR contributions to MHSR.

Although there are many promising areas for OR in MHSR, the meeting focused on four major areas:

1. Modeling of need, demand, and utilization in MHSR;

2. Modeling and conducting program evaluation in MHSR;

3. Modeling resource allocation in MHSR; and

4. Modeling large-scale system interactions of the mental health sector with other major societal sectors, such as the general health care system, the criminal justice system, and the financing system for health.

These areas were chosen because they are significant in understanding the problems and systems aspects of MHSR, and also because OR has made some contributions to this area and similar areas in the general health care system. Papers were presented in each area. After presentation of the paper, two or three discussants addressed issues in the paper, raised new issues, and helped clarify the role of OR in MHSR in regard to these issues.

II. GENERAL CONCLUSIONS

Operations research as a paradigm has the potential for aiding decisionmakers in improving the planning, management, and operation of the mental health service system and its interaction with other systems. Problems and issues are approached by understanding the system being studied, that is, defining the objectives or goals of concern, the flows of people, the facilities and processes within and outside the system, the inputs to and outputs from the system, and the data needed to develop OR models of the system. A powerful advantage of OR analysis and OR models in MHSR is their ability to provide comprehensive data reduction on complex systems by capturing the system's logic. After the data are gathered and synthesized and the model of the system developed, OR methodologies are used to aid in decisionmaking processes and in better understanding the dynamics and operation of the system.

These methodologies have been used in many other sectors of the economy, including private industry, military, and government and other public sectors. OR's contribution to the resolution of problems in MHSR is twofold: improved efficiency and effectiveness of the delivery of mental health services, and improved understanding of the mental health system through quantitative modeling of this system and its interactions with other systems.

Because operations research is grounded in quantitative model building and systems analysis, it has limitations. We will briefly point out some limitations before going on to those research areas in which we believe operations research can make a substantive contribution.

First, it may not be possible to build quantitative models in some cases where the important descriptors of the systems involve subjective considerations that are not quantifiable.

Second, the assumptions necessary for the available models may be unrealistic, and it may be extremely difficult to build realistic models for certain problems. For example, optimization models work well only when the decisionmakers have identified objectives as well as constraints. Simulation models must also have well-identified transfer relationships in either a probabilistic or a deterministic sense.

Third, data requirements of the models may be far greater than data availability. In this case, implementation of the model would be precluded although indications of need for future data collection would be useful.

Finally, operations research models should be thought of as aids in the decisionmaking process rather than as the decisionmaking process itself.

With these caveats in mind, it is still possible for the paradigm of operations research to be applied successfully to some important problem areas in mental health services research. However, an important point must be made here. Most mental health problem areas are complex and require knowledge from many disciplines for their solution. For OR to have its maximum impact on most of these complex problems, it is essential that, from the very beginning of work on a problem, an operations researcher be an integral part of a team that includes medical sociologists, mental health professionals and administrators, behavioral scientists, economists, computer scientists, epidemiologists, statisticians, and others, as appropriate. No one person can amass sufficient knowledge to handle these problems alone. For example, to quantify what in many cases seem nonquantifiable variables, the interaction of operations researchers with behavioral scientists, medical researchers, and others is needed. However, such interaction must occur at the inception of programs to be useful at a later stage.

As a background to the meeting and as a description of the early work in OR/MHSR, the annotated bibliography compiled by Jack E. Scott (Volume II) has been a valuable aid. A similar activity should be undertaken describing the location and types of available MHSR data. At present, there are some survey reports and scattered information about available data sources. For many models we would like to build, the available data may not be adequate or perhaps may be in the wrong form, and surrogates would have to be used. Furthermore, all current data sets would have limitations in supporting large-scale and sophisticated modeling efforts. Nevertheless, exploratory OR studies in many of the areas discussed later in this volume, and some extensive studies on a national basis and in selected locales, can be undertaken with existing data. Consequently, an inventory of existing data and their actual and potential use should be prepared soon by or with an operations researcher. It also may be useful to develop a portable data base from both the NIMH research projects and the research projects using mental health data made available by various agencies of the Department of Health and Human Services. This data base could be made available at cost to all researchers interested in OR/MHSR problems.

According to meeting participants, if a research program in mental health services research is to be effective through NIMH's Division of Biometry and Epidemiology, there should be an operations researcher on the research grant study section. The study section needs such a member to help evaluate proposals with OR content.

III. SPECIFIC RESEARCH ISSUES FOR OR/MHSR

Meeting participants discussed many research issues lying at the interface of operations research and mental health services research. These issues involved using OR approaches for system understanding, system description, model building and decisionmaking, policy analysis, and decision support systems activities considered traditional aspects of OR studies. Some less traditional and somewhat surprising activities suggested were assessment of patient needs and the relative importance of program objectives. These latter activities could be undertaken jointly with research team members from other disciplines.

A. Modeling Need, Demand, and Utilization in MHSR

Any examination of the mental health service system begins with an analysis of the concepts of need, demand, and utilization. In the present context, utilization refers to the provision of service to a client. Demand represents the expressed desire of a client for services. Need refers to the presence in an individual of a pathological condition amenable to treatment. The latter concept of need is most often considered an epidemiologic concept, while demand for and utilization of services are considered to fall within the province of health services research. The major question is, What models can accurately describe and relate need, demand, and utilization of mental health services? It is important to note the interrelatedness of these three concepts, because changes in the mental health service system that affect demand and utilization may induce major shifts in needs for services. The major challenge for OR is identification and development of models that can accurately describe and interrelate need and demand for and utilization of mental health services. Operations research, in conjunction with other disciplines, can make significant contributions in assessment of methodologies and in the characterization of the relationships between need, demand, and utilization.

The results derived in this area will provide basic data and modeling inputs for the work on program evaluation, resource allocation, and large-scale systems interactions. Consequently, the data and models not only must be appropriate for the decisions of interest later but also must be clearly specified with regard to the definitions used and the interrelationships discovered. Fortunately, NIMH has recently completed a study of the definitions of mental disorders, and it is available in the _Diagnostic and Statistical Manual of Mental Disorders (Third Edition_, 1980).

In addition, epidemiological studies on incidence and prevalence of many mental health diseases have been completed or are under way. These studies describe the medical _need_ for mental health services. There are still major questions relating the demand and utilization of mental health services to need. As in all health care, utilization depends not only on incidence but also on such constraints as reimbursement mechanisms, accessibility, quality of care, and an often ill-defined relationship between treatment and outcomes (i.e., cause-and-effect relationships in the treatment setting). When collecting data on demand and utilization, we usually deal with existing programs and institutions. Consequently, the data are confounded by such factors as censored samples, very long periods to achieve steady-state conditions (after 3 to 10 years in certain chronic care settings), and the difficulty of separating the underlying stochastic mental health process from the transient effects of policy changes in the system. Some of the modeling techniques and systems analysis methods of OR may prove useful in understanding these relationships.

Participants at the meeting discussed these and other aspects of need, demand, and utilization. Some of the major research projects suggested by participants for applying operations research follow.

1. Build general OR models of demand and utilization involving such factors as reimbursement regulations, accessibility, available manpower, facilities and programs, general health treatment centers, and demographic trends.

The following OR methodologies could be considered: analysis of variance and regression, cluster analysis, marketing assessment, econometric models, time series models, Markov or deterministic flow models, subjective probability models built in delphi or nominal group-process techniques, and multiattribute utility models.

2. Use mental health definitions of specific diseases and epidemiologic studies of incidence and prevalence to assess the level and variability of demand (perhaps its probability distribution across the population and across

time) at various entry points in the system. In this way, researchers can determine bottlenecks for potential new programs or policies. OR methodologies of interest are parametric network flow models, which would relate medical need to demand and to utilization, and statistical and probabilistic models of causal and/or distributional relationships. Monte Carlo simulation would be of great use.

3. Assess the utilization of chronic care mental health facilities. OR models are needed to handle superimposed transient and long-term patients and the effects of changing policies, such as deinstitutionalization. Some methodologies of interest are Markov models and simulation.

4. Assess the use, validity, and cost of hybrid models that measure the interacting components of need, demand, and utilization. Many of the above-mentioned methodologies, as well as cost-benefit and cost-effectiveness methods, are applicable.

5. Build a long-term data collection system to meet needs for decision support. There are needs for management information systems, decision support systems, and knowledge of the man-computer interface, in addition to some previous methodologies.

6. Build resource consumption models based on case mix and severity measures for utilization research. Resources consumed are the manpower, facilities, technologies, and supplies used to diagnose and treat the disease. OR methodologies involve patient-flow models, resource consumption grouping models, and simulation.

OR researchers should work with mental health researchers, epidemiologists, and behavioral scientists to form the definitions of medical need, demand, and utilization appropriate for later models of resource allocation and large-scale mental health system interactions. The required data for these descriptive and decision models may require different definitions for different purposes. For example, "need" may at times include physician-defined medical need and at other times patient-defined need (possibly not medical), because each has different utilization relationships.

B. Modeling and Conducting Program Evaluation in MHSR

As noted in the preceding section, there are complex relationships among need, demand, and utilization, as well as among diagnosis, treatment, and outcome, that are not understood well. How then should we go about assessing and understanding the effectiveness of mental health services? How do we evaluate the relationship between treatment and outcome?

The mental health literature contains examples of attempts at conceptual models of program evaluation. Most of the approaches and designs in studies of program evaluation, however, have used experimental or quasi-experimental models of defined client populations. Classical experimental design (such as the analysis of covariance with randomized treatment) has been useful in many studies in agriculture, health, and industry. But even in these settings it is essentially a two-fixed-point observational approach (pre- and post-treatment) and does not capture the intermediate dynamics of change.

In many cases, these dynamics are not important. In mental health program evaluation, however, the dynamics most often provide critical insight into the value of programs. Furthermore, given the current reluctance to deny potentially helpful treatment to individuals, the controlled clinical trial implied by the classical design is difficult to justify if one treatment is presumed to be superior. One way around this difficulty is to use quasi-experimental designs, but the statistical validity of conclusions may suffer from lack of randomization. Neither does this approach capture the dynamics of the treatment-outcome process. (Situations exist, however, where the experimental or quasi-experimental design models are appropriate and effective.)

Models that capture the dynamics of the stochastically changing treatment-outcome process are coming into greater use. These models measure the (usually probabilistic) flows of patients. Markov, semi-Markov, and simulation models are the most commonly applied. The data requirements may be great because the movement of patients between states must be accurately measured. The participants at the meeting discussed these and other aspects of mental health program evaluation. The following research goals were suggested:

1. Define clearly the objectives of any program to be evaluated. The OR researcher, in conjunction with mental health researchers, behavioral scientists, administrators, government executives, and legislators, must know clearly what is to be achieved with whom; otherwise, the program will be difficult or impossible to evaluate. This should be done at the start of the program. Useful OR methodologies are delphi, nominal group technique, priority weighting, conjoint analysis, and other multidimensional scaling techniques.

2. Study the cause-effect relationships between diagnosis, treatment, and outcome. OR should work with mental health researchers in the development of severity indices and multidimensional measures of outcome by different treatment modalities and locales. Essentially, this work is defining the flow of patients through a stochastic process and all the possible states at each stage (beginning, intermediate, and final). The OR methodologies that could be used are Markov and semi-Markov chains or processes. Subjective probability estimating techniques could be extremely useful here.

3. Develop data systems, including data collection and management information systems structured efficiently for regular periodic recording and, usually, computerization. If possible, patient tracking or linkage across the general health system and other social systems should be entered into the data base. OR methodologies to be used are decision support systems, including management information, validation, and computer file structuring systems.

4. Define the linking of a sufficiently broad battery of program performance and patient functioning measures for a thorough program evaluation. It

is necessary for the OR researcher to be a member of a multidisciplinary team for the construction of scales. OR methodologies listed in items (1) and (2) are applicable here for the mental health aspects and cost aspects using accounting and financial management measures and techniques.

5. Develop stable baseline transition matrices that represent the epidemiology and natural history, in a medical sense, of mental disorders against which to measure change. This work closely relates to item (2). If we can develop such matrices, there is less need for the clinical trials approach to program evaluation. If a new program for a given disease, severity, or other factors has a different set of transition probabilities, inferences about the program may be drawn. It should be noted that for many mental disorders there may not be adequate data for estimation of stable baseline transition matrices; however, it may be feasible for a few mental disorders, e.g., schizophrenia. OR methodologies of interest involve the use of observation and statistical analyses by means of "intensive" or "extensive" design. Basic statistical research is also needed in the area of covariate adjustment in stochastic processes.

6. Investigate ways to handle the missing data problem from partial or incomplete patient-flow observations. A similar problem exists with aggregate data analysis when all that is known is the proportion of a cohort visiting in a certain state at a given time. OR methodologies of interest draw from statistical inferences and from sensitivity analysis.

7. Conduct parametric analysis on the transition matrices and other coefficients in the models. Useful OR tools are simulation, topics from mathematics such as analysis and topology, and statistical analysis of the variation in estimated parameters. Subjective estimates and expert opinion may prove useful here also.

8. Investigate macro approaches to overall system or program evaluations before making decisions to implement, terminate, or replicate programs. A very useful OR methodology for this purpose is decision analysis with objective or subjective bayesian estimates of the probabilities involved. This approach could be combined with a deterministic flow model in the decision process.

9. Investigate the cost-effectiveness and applicability of experimental, quasi-experimental, stochastic process, and decision analysis or process models for use in program evaluations. What are the objectives, decisions, information needs, and constraints that make one model more appropriate than another? This research involves an evaluation of the program evaluation methodologies in various MHSR contexts themselves.

C. Modeling Resource Allocation in MHSR

Modeling resource allocation decisions in MHSR require as inputs the results from need, demand, and utilization research, and both inputs and state-variable output of the program evaluation. Much of the data collection, patient-flow, and outcome-measure research efforts suggested in the previous section must be developed with an appreciation of how this information will be used in resource allocation decisions. Too often, the work done and the data obtained in one research area are not useful in another, but could have been if they had been given prior thought. The interaction of other research and data sources becomes most apparent in the resource allocation area.

The major question addressed in this section is the determination of the resource mix (facilities, programs, and manpower) that will deliver the most effective array of mental health services to a community, State, and Nation. Although some of the constraints on and objectives of mental health services are easily modeled, many behavioral, social, and political constraints and objectives require a great deal of basic research. Because of multiple objectives and "binding" versus "fuzzy" constraints, the modeling of resource allocation (although in many cases straightforward) presents some interesting and difficult research issues. Short-term operational and long-term planning models useful in mental health services must be defined and assessed. These models are needed at the institutional level and, perhaps more importantly, at the regional, State, and national levels. Much of the funding of mental health services and new programs comes from the State and Federal level and is influenced by overall planning and allocation of funds. Thus, models are needed to provide these allocations in the most cost-effective manner with appropriate consideration of access to and quality of availability of mental health care.

What has been missing to date is a clear understanding of which decisions are important at each level, who the decisionmakers are, what are the criteria and objectives controlling their decisions, and what types of models best support these decisionmaking processes. To aid decisionmaking, we must develop easy-to-use interactive computer programs that automatically access appropriate current data bases, produce useful management information, flag potential problem areas, and make recommendations for resource allocations. Some of the research goals and methodologies for resource allocation suggested at the meeting follow:

1. Describe the existing system by looking at the flow of resources (facilities, programs, manpower, dollars) in mental health care at the local, regional, State, and national levels. Also, determine the types of decisions that allocate the greatest proportion of funds and have the greatest potential for health impact. This systems analysis work will lead to the development of objective functions, constraints, and transfer functions needed later. A considerable amount of data already exists, particularly at the Federal level, although the relevant material must be coordinated and understood.

2, Build models to aid in decisions at the Federal level concerning the allocation of funds to direct and indirect care (services, treatments, facilities, programs) and research and demonstration. Appropriate OR methodologies are mathematical programing, simulation, scheduling, and hybrid models.

3. Model the manpower needs by specialties with regard to the allocation of funds at the Federal level for training and education and services for the

disadvantaged. This also involves determining the appropriate mix of manpower categories for the needs, demands, programs, and institutions developed in the preceding areas. Useful OR methodologies are forecasting (time series, regression, subjective estimation), mathematical programing, and Markov decision models.

4. Model the optimal mix of Federal, State, and regional resources between prevention and treatment sectors of mental health services based on objectives, constraints, and transformations discussed in item (1). Here again, mathematical programing, simulation, input-output, and econometric models would be useful.

5. Conduct more basic OR research in large-scale multiobjective programing with application to MHSR. Basic methodologies needed here are mathematics, statistics, computer science, and the theoretical background areas of OR.

6. Collect and evaluate the resource allocations and consumption regarding the hundreds of Health Systems Agencies plans in the country. (This effort also fits into item 1 above.)

7. Model the optimal resource needs and allocations at the State level among inpatient long-term and acute psychiatric care, community mental health centers, nursing homes, and other institutional and noninstitutional settings. This modeling should consider the optimal mix of Federal, State, regional, and local funding of this care. OR methodologies are mathematical programing, simulation, and Markov decision processes.

8. Build planning and allocation models for State, regional, and local manpower and facilities. The models should parallel those discussed in item (7) and could use the same OR methodologies as well as forecasting models.

9. Construct on a more micro and detailed level, local and regional planning models of items (7) and (8), using similar methodologies.

10. Build interactive support models for operating ongoing programs or institutional systems. These models would do patient and personnel scheduling and allocation, facility location and sizing, inventory management, diagnostic decision aiding, and treatment protocol management. Case studies might be useful here before construction of a model. Many of the previously mentioned methodologies, as well as decision analysis, subjective probability analysis, and other behavioral techniques, could be useful. Some of these types of interactive support models are currently being used in general acute health care institutions.

D. Modeling Large-Scale Systems Interactions

A major task facing many mental health planners is how to conceptualize, organize, and operate a mental health care system that can provide cost-effectively the full range of services required by the Nation. To accomplish this comprehensive goal, it is imperative that the mental health planning efforts emphasize the importance of increasing interaction and interdependence among government agencies, other service delivery organizations, and the people needing, providing, and financing the care.

The major question in this section is, What is the nature of the interdependence of the mental health service system and other social service systems (e.g., criminal justice, general health care, alcohol and drug abuse, and education)? It has been clearly demonstrated that some individuals with mental disorders are often not seen over long periods of time in the specialty mental health sector, because they tend to use the general health care system and other social systems. Indeed, there is evidence that persons with mental disorders who also use the general health care sector utilize it twice as intensively as patients not diagnosed as having mental disorders. Characterization of these interactions between large-scale systems is extremely important in view of certain current trends in health care services in the United States. In addressing such issues as national health insurance and the increasing size of the privately funded mental health service system, it is particulary important to model large-scale systems interactions.

Data needed for modeling large-scale systems interactions may be difficult to obtain, however, because of the complex way patients move through the various systems. Movements, treatments and outcomes, and the budgetary facilities and provider personnel define the transformations and interactions among the systems. If it is possible to define these macrolevel flows, better planning and treatment of mental disorders may be possible. Important dynamic trends (and, possibly, cycles) of health care services also affect the delivery of mental health care. Many of these trends are characterized in table 1.

These trends have strong effects on the specialty mental health sector--state and county mental hospitals, private mental hospitals, hospitals with psychiatric units, community mental health centers, private practice psychiatrists and psychologists, and other mental health treatment centers and providers. They also affect the general hospital, nursing home, and primary care sectors; other human services and social sectors; and the criminal justice, education, and welfare sectors. As a result, of course, the budgetary and resource allocation policy and decision processes are affected.

To improve policies and decisions, research is needed to understand these large-scale systems interactions. Smaller research projects would perhaps have a higher short-run payoff in ability both to understand and to affect decisions in the mental health system. Large-scale mental health system models or models of interaction with other systems would be costly to develop. Although these latter models are essential for total system understanding (and have been suggested by others over the past decade), they involve a large commitment of funds and a highly skilled team of people who can work together on large projects.

Similar large-scale systems are available in the U.S. Department of Energy, the military, and private industry. These have been developed at the

Table 1. Important recent trends for U.S. health care services

STRUCTURAL DELIVERY SYSTEM CHANGES

- Long-term to short-term
- Inpatient to community-based
- Increase in general hospital beds
- Increase in third-party coverage

DEMOGRAPHIC SHIFTS

- Increase in percent and number of aged
- Increase in high-risk adolescents

SOCIAL PROBLEM SHIFTS

- Increase in crime rate
- Increase in alcohol and drug use rate
- Increase in divorce rate and family fragmentation

ATTITUDE SHIFTS IN GENERAL POPULATION

- Increase in acceptance of mental illness
- Increase in interest in informal self-help systems

COST-CONTAINMENT PRIORITY IN PUBLIC POLICY

- Increase in emphasis on cost, access, and quality
- Increase in high estimates of economic burden of mental illness

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expense of many man-years and millions of dollars. For this reason, a good approach would be to build a conceptual framework and conceptual modeling effort for such large-scale systems to understand the data needs, data flows, tranformations, objectives, and constraints of the systems as well as the dynamic factors affecting each element of the total system. This first stage would not include building the actual large-scale models themselves. Instead, it would start by building and implementing submodules of specific aspects of the mental health service system itself. Although large-scale system models are needed, the current data base and levels of funding may not be appropriate.

The meeting participants formulated the following research goals:

1. Design large-scale systems flow models of the mental health interface among the mental health sector and other sectors at the national and State level. The decisions would be the policies affecting and affected by the trends in table 1 and the flow of mental health patients into and out of the various sectors. It is necessary to define the transformations and

constraints, including budgetary and reimbursement, and to evaluate different optimal decisions and their consumption of resources for various objectives. OR methodologies of interest are mathematical programing, simulation, systems analysis, forecasting, subjective estimation, Markov decision flow models, and econometric input-output models.

2. Use models of the large-scale system designed in item (1) to build subsystem modules that could interact with or provide input to the macro model. some of the subsystem modules could come from the models suggested in the preceeding sections, and others could come from models built in other sectors, including alcohol and drug abuse, criminal justice, welfare, and education (e.g., schools for the mentally retarded).

3. Provide analysis and evaluation for data collected in the areas of retardation among the various systems. Again, this work should involve an operations researcher to provide the broad systems analysis perspective for future modeling efforts. Pertinent OR methodologies here are systems analysis, decision support systems, and statistical techniques.

4. Build models representing flows or transfers between the mental health sector and one other sector. These models would also be modules for the large-scale system interaction studies mentioned in item (1). Special emphasis should be placed on a model relating the mental health sector to the general health sector. This model is needed because there are many important interactions involving treatment, facilities, personnel, and financing. The OR methodologies in item (1) would also be appropriate here.

5. Conduct research on the implementation and use of large-scale interactions models for planning, policy, and decisionmaking. Evaluate the models' validity, efficacy, and sensitivity to address political and behavioral issues. This work on model validation for decisionmaking is similar to the program evaluation work to be described in the next section, and some of the same methodologies apply. (The DOE is doing much work in this area in regard to large-scale energy planning models.)

6. Investigate the dynamics of primary and secondary effects of the trends in table 1 on the mental health sector. Appropriate methodologies are analysis of variance, regression, feedback flow models, and subjective decision analysis techniques.

IV. CONCLUSION

The mental health services research area is rich in interesting, important topics for research and implementation that lend themselves to the application of operations research approaches and methodologies. This meeting produced a list of research projects in four promising areas important in the interface between operations research and mental health services research. It is hoped that not only researchers in OR and MHSR, but researchers and administrators in the Federal Government--especially the Alcohol, Drug Abuse, and Mental Health Administration and NIMH--and State governments and agencies as well will find these results useful in allocating some of their efforts to support research and implementation on these topics.

Chapter 1.

NEED, DEMAND, AND UTILIZATION MODELS FOR THE MENTAL HEALTH SYSTEM

James Reuter, Sc.D., and David H. Gustafson, Ph.D.

I. INTRODUCTION

As we proceed from one decade into the next, it is probable that most people have given some thought to what the next 10 or 20 years will bring. In regard to the mental health system, it is likely that critical turning points will be passed during the next two decades. The most important turning point will include passage of a national health insurance scheme and resolution of issues concerning coverage for mental health services. The effects of decisions in this area alone will define portions of the basic structure of the mental health system for years to come. In anticipation of these changes, and in recognition of the effort necessary to design, operate, and control such a system, policymakers are beginning to explore the value of a variety of techniques for assisting in policy, planning, and evaluation efforts. The intent of this conference was to focus upon the utility of the techniques generally grouped under operations research (OR) and systems analysis.

This paper considers the development of systems models of need, demand, and utilization of mental health services. Obviously, any attempt to plan, evaluate, or manage a service delivery system must begin with an understanding of the needs the delivery system is attempting to meet, the types of services to be provided, and the number of units of care that can be delivered and consumed. The descriptive nature of the models to be discussed answers the who, where, what, and when of these questions.

During the development of this document it became clear, however, that our presentation had to go beyond a critical evaluation of descriptive models of need, demand, and utilization. In much the same way that distributional factors contribute to the specification of an appropriate statistical test, the peculiarities of need, demand, and utilization should contribute to the design of models for evaluation and policy studies. We describe some of these critical characteristics. It is our position that systems models can clarify the processes that produce need, demand, and utilization of mental health services. Although beyond the scope of this paper, applications of systems models and operations research can also contribute substantially to the evaluation and analysis of policies that affect those processes.

Discussion of specific models requires definition of need, demand, and utilization. Although we all probably have an intuitive sense of these terms, their meanings can vary with the context in which they are used. Of the three terms, utilization is the best understood. Utilization of services implies the consumption of a resource, that is, provision of a service to a client. However clear the definition, though, its application to mental health services is not clear because the scope of mental health services is not always consistently defined. We consider this problem in more depth in a later section of this paper.

The concepts of need and demand are much more difficult to define because their meanings vary and overlap. Within an epidemiologic context, need is defined as the presence of a pathological condition; incidence and prevalence rates are frequently used as measures of need. Beyond such epidemiologic usages, however, the term also implies a need for something; in a health services delivery context, it implies a need for therapeutic services. Unfortunately, this implication supports the commonly accepted linkage between a client's condition and the therapeutic intervention. This linkage does not always exist in the mental health service system.

The concept of demand for mental health services overlaps the concept of need for such services. In the mental health literature, demand is used for both expressed and unexpressed demand for services. In this paper, we restrict our use of the term demand to indicate expressed demand, and we refer to unexpressed demand simply as need for services.

Finally, we must clarify two arbitrary limitations we have placed upon the scope of our work. First, we do not discuss statistical models of need, demand, or utilization even though there are many important statistical models, especially in the area of need and needs measurement. Although statistics is a frequently used tool of operations researchers and systems analysts, the subject matter that would require coverage is beyond the scope of this paper. Second, although all of the models we discuss can make valuable contributions to prescriptive studies (for example, evaluations, policy analysis, and administrative decisionmaking), our presentation is limited to the descriptive uses of the models and their implications for prescriptive analysis. Obviously, description is a basic element of any well-designed study regardless of the eventual goal of the research. Because this paper is intended as only one element in a broader context, we leave the prescriptive uses of these models to be discussed elsewhere in this volume (Chapters 2 and 3).

II. MODELS OF NEED AND DEMAND

The determination of levels of need and demand is a central question that must be confronted in mental health services research. Any discussion of program evaluation, resource allocation, or policy considerations must be based on a clear understanding of what the needs and demands for services are, what the treatment alternatives are, and how well those needs and demands are met. Both concepts are related to the input and output of programs. Theoretically, treatment programs are designed to address specific needs. Program output (i.e., treatment outcomes) can be altered by changes in the demand or need for services. Similarly, changes in program outputs can, and ideally would, lead to changes in the nature of the demand and need for services.

Although the determination of needs should be a prime focus of studies, the traditional method for measuring needs (i.e., diagnoses) falls far short of the mark. Psychiatric diagnoses are notoriously unreliable, as demonstrated by test-retest studies. Also, the need of a client for mental health services goes beyond traditional diagnostic schemes based upon the classification of pathology. For example, a psychotic individual's true needs for services will reflect not only the nature and severity of the disorder, but also such factors as the extent of available support mechanisms (e.g., family-related variables) and the patient's life style (e.g., employment status).

Various techniques have been used to find alternative approaches for measuring need for mental health services. These techniques have relied predominately upon the statistical analyses of data, e.g., cluster analyses, factor analyses, multidimensional scaling techniques, and similar approaches. Most recently, these techniques are being used to improve the diagnostic classification used by clinicians and to incorporate more social and behavioral characteristics into the specification of a patient's condition. The results of these efforts, as presented in the Diagnostic and Statistical Manual of Mental Disorders (3rd Edition 1980) (DSM-III), are now coming into use (see Mezzich 1979 for a description of the analysis).

In this paper, we present alternatives to these statistically based classification schemata. These alternatives are called multiattribute utility (MAU) models and subjective probability models. These techniques provide mechanisms for incorporating the judgmental character of needs and demands for mental health services directly into models. Since these models do not depend on large, specially collected data sets, they are relatively easy and inexpensive to construct and use.

A. Need as a Judgmental Concept

In health care, need is often considered to be an epidemiological concept; that is, there exists some specific condition that can be observed (at least statistically) and that represents a need for a particular treatment. One can measure a community's need for some service, and document changes in that need across time and between communities. The measurement of need for alcoholism, drug abuse, or mental health (ADM) services, however, has significant judgmental components.

The impact of subjective judgments in determining mental health needs arises in several ways. First, a need for services implies a clear benefit from a specific intervention. For ADM services, these benefits may be unclear. Even if professionals agree that a certain degree of need exists, there can be substantial disagreement as to what services would meet that need. Some people believe in one type of therapy or service, while others believe differently. These differences of opinion carry over into the determination of treatment goals. For example, Alcoholics Anonymous believes that abstinence is the appropriate goal of treatment for alcohol abusers; others consider responsible drinking behavior a more reasonable goal. Obviously, if the goal of treatment becomes a matter of opinion, then the outcome of treatment also takes on a subjective flavor. Whether a particular form of treatment is successful in meeting a need may depend upon what one judges to be an appropriate outcome. Finally, the definition of need (and appropriateness and outcome) is responsive to political processes. It is common for funding priorities to be determined within the political arena. Thus, the level of need perceived by decision-makers (and the determination of an appropriate response to that need is influenced by the comparative strengths of various pressure groups. This is not all good or all bad; it is the way the system currently works. As long as the concept of need remains subjective within the professional arena, it will most likely retain its political flavor as well.

Given the current pervasiveness of judgmental factors in determining the need for ADM services, there are several paths toward development of a model. First, one can initiate or continue to support epidemiological studies and treatment evaluations designed to reduce the impact of judgment and opinion, on the determination of needs. It should be recognized, however, that these approaches will probably not produce any revolutionary results in the near future (i.e., within 5 years). Although we advocate continued investment in research of this type, we feel that operations research need not await the results of such studies to make an effective contribution to mental health services research. We believe that operations research can materially improve the ability of the mental health field to work with the subjective character of need and demand for mental health services.

An operations research approach would recognize and accept that, for the foreseeable future, need and demand will retain their subjective components. This assumption refines the problem. Now the basic issue becomes how to incorporate subjectivity into the needs measurement process. There are a number of techniques for accomplishing this, including statistical analyses, multi-attribute utility models, subjective probability estimates, and nominal groups processes. The basic unifying concept of these methodologies is their intent to improve, rather than replace, the subjective judgment process. Decision analysis techniques identify, quantify, and aggregate the elements upon which a judgment is based. In doing so, the analysis frequently clarifies the judgment process and resolves conflict that can arise when the process is not understood. The judgment process is also improved by focusing the best available expertise on small, manageable aspects of the process.

Group process techniques elicit judgments and promote consensus. The combination of decision analysis and group process techniques can result in judgments far superior to those made in the absence of such techniques. Clearly, this approach represents a radical change in the focus of research and development efforts from the recipients of care to the individuals making decisions about the care.

B. The Case For and Against Subjective Models

Several points concerning subjective judgments need clarification. First, we are encouraging the use of subjective judgments as elements in a disaggregated decision model. We would be the first to admit the failings of human beings in making complex judgments. However, it has been shown in numerous field and psychological studies (Slovic and Lichtenstein 1976) that experts can make reliable estimates of the components and the relative importance of each component that contributes to decisionmaking. For example, our research shows that psychiatrists are relatively ineffective at identifying individuals who intend to commit suicide from the larger set of clients who express suicidal thoughts (Gustafson et al. 1977). Clinicians, however, use their judgment to respond to the following kinds of questions: Of two individuals, one who will make a suicide attempt and one who merely expresses suicidal thoughts, which is more likely to live alone? How much more likely? Thus, panels of experts provide their best judgments of the relationship between the disaggregated diagnostic information (e.g., living alone) and the hypothesis of interest (e.g., suicide attempt).

At this stage in the subjective modeling process, operations researchers can play a significant role in resolving two common problems. First, establishing a consensus on issues being considered can be a problem. As previously suggested, opinions on the need for ADM services may vary. If there is no apparent consensus, the modeler must develop some form of consensus. This can be accomplished in a number of ways. Delphi, nominal group, and consensus group techniques can assist when the range of opinions is relatively small or when the opinions are at least not in direct conflict to one another. These techniques are also useful in eliciting an initial set of judgments. Often, lack of consensus results from legitimate disagreement between two constituencies. The tools of utility theory and conceptual modeling and the concept of Pareto optimality can be used to understand the conflict. In effect, one develops and uses several utility functions, each representing the values of different constituencies to create and evaluate alternative treaties. This information can then be injected into the negotiations to help opposing factions understand the roots and implications of their conflict, thus aiding in its resolution (Gustafson et al. 1980).

A second problem, which operations researchers are trained to address, is that of quantifying the judgments accurately. For example, it is known that judgments made by groups of experts using a process called ETE (estimate-talk-estimate) lead to probability estimates superior to group processes where consensus is reached. The ETE process is also superior to estimates by individual judges (Gustafson et al. 1973). We also know that people tend to underestimate the value of highly diagnostic information and overestimate the value of nondiagnostic data. Tools have been developed to get around these problems. Other characteristics of the human judgment process are well described by Hogarth (1974) but are not addressed here. The point is that the process of obtaining subjective estimates is nontrivial, and OR modelers skilled in this process should be fully utilized.

The second phase of the development of subjective models is the aggregation of the specific judgments into a decisionmaking model. Statistical models (such as Bayes' theorem), utility models, and optimization models are needed to combine judgments on several diagnostic factors in order to recommend a decision. Thus, the suicide model mentioned above has 38 factors (such as living status, employment status, etc.). Experts provide estimates about the impact of each factor. A Bayesian model combines factors that relate to specific patients and predicts probability of a client's attempting a suicide. Thus subjective judgments as well as an aggregation model are needed.

Finally, although the preceding discussion emphasizes the use of judgmental variables, hard data should also be used whenever possible. Empirical data should be provided to the experts making the judgments, if relevant data are available. The development of the aggregation model, and its validation, may also depend heavily upon empirical evidence. We advocate using both subjective judgments and empirical data--not just one or the other. One of the obvious advantages of a subjective approach, however, is that it allows the decisionmaker to improve his or her decisionmaking, even when no data are available.

As is true of any model, the measurement of need or demand as a function of expert judgment has both advantages and disadvantages. The major drawback of these models derives from the inherent limitations of judgment. Traditional approaches to decisionmaking represent, more or less, a search for basic truths. They are built upon the assumption that there exists some underlying cause-and-effect relationship between need, treatment, and outcome. The challenge is to be clever enough to find and estimate these relationships. In judgment methodologies, one is not so directly concerned with facts. Thus, the drawback of these techniques is that there is always the possibility that our presumed knowledge is wrong.

Judgmental models in this case would be a pyramiding of fallacies. On the other hand, psychiatrists and therapists use their own opinions every day to make decisions about patients' needs. If their opinions are "good enough" within the complex context of direct patient care, they should be even better when the complexity of the problem is reduced by means of a model that disaggregates the problem and requires judgments on only one component of the problem at a time. Thus, although judgment methodologies will not reveal any new facts, they can reveal the rules under which the system currently operates. For many applications, that degree of exactness suffices.

Despite the inherent drawbacks of basing decisions on subjective judgments, we believe that judgmental models have many significant advantages over empirical models. First, these models and sources of data are readily available. Although they are not based in rigorous scientific facts, neither do they require that we wait for those facts to be established. The mental health system will continue to operate whether or not we sensibly evaluate and allocate resources. These methodologies allow us to seize existing opportunities to apply the best knowledge available to a wide spectrum of problems.

Second, judgment models are inexpensive to develop and maintain. Consensus techniques need not depend upon large, longitudinal data bases. The basic input data are drawn from the accumulated experience and knowledge of professionals in the field as well as from existing data sources. As a result, they can be ideal in situations demanding a quick response.

Third, judgmental models offer great flexibility. They have been used to address a broad spectrum of issues. Judgment models have been used at the macro level to provide gross indices of medical underservice. On a micro scale, these models have been used to estimate the severity of individual cases, to develop treatment alternatives, and to create diagnostic aids. In a different context, these models have also been used to evaluate progress in health and social services and to negotiate political differences.

Fourth, these models generally are quite accurate. A suicide prediction model (Gustafson et al. 1977) has proved substantially more accurate than clinicians in identifying persons who attempt suicide. Severity-of-illness indices based upon multiattribute utility models have proved remarkably consistent in performance, even when developed by several different individuals or groups (Gustafson and Holloway 1975). The Index of Medical Underservice (Health Services Research Group 1975) has been subjected to a series of evaluations over a several-year period with satisfactory results.

The fifth advantage of subjective methodologies derives from the assumption that most mental health decisions are made with less than the best expertise. Some mental health practitioners are far better than others at making judgmental decisions. Yet all of these people make decisions. Subjective judgment processes give us the opportunity to capture the knowledge of the best people in the field and make that knowledge available to all. In the suicide model discussed above, subjective estimates made by a team of nationally respected experts on suicidology are stored in the computer. Each time a new patient is presented to it, the computer draws on the appropriate judgments in storage. The opinions of these nationally respected experts are available to all who use the system. Of course, these estimates can be modified by new empirical data or by a new set of experts.

The final advantage of consensus models to be mentioned here is a corollary to the preceding five. If there exists a cheap, readily available, and flexible model of need, then we need not await the specification of a single, all-purpose model of need. We believe too much homage has been paid to the concept of an all-purpose, multidimensional scale for measuring need. It is our bias that this emphasis may be inappropriate. For certain questions, the key factor may be severity of illness. For other questions, the most important factor may be the character of the disorder (i.e., traditional diagnoses). In still other situations, the match between treatment and need may be of prime importance.

It appears that requiring any single scheme to meet all of the demands placed upon it may be excessive. Even within a single area, one all-purpose index may be inappropriate. A severity index model to measure an individual patient's need for services may not be the same as a severity index used in a retrospective evaluation system. Judgmental models are a readily available alternative; namely, a quick, easy, inexpensive way to develop need and demand measures to fit the requirements at hand. Although the models will not always produce better results than empirical models, their ease of use and their readily available data sources (i.e., expert opinion) may make them more effective in the long run.

C. Applications of Operations Research (OR) to Models of Need and Demand

Myriad opportunities exist to use operations research methodologies in the development of models of need and demand. In the area of empirically based models, OR practitioners have a long involvement with the development of needs assessment and patient classification methodologies, for example, cluster analysis. If the eventual use of these measures of need and demand is in a complex system model such as those described in a later section of this paper, operations researchers certainly should be involved from the onset. Thus, although the emphasis in this paper has been on subjective models, we hope that the reader recognizes that OR practitioners can also provide a great deal of assistance with the more traditional approaches.

Operations research has already contributed substantially to development of subjective models for measurement of general health and mental health needs. The existing literature includes examples of the development of patient assessment instruments and treatment selection models. Examples of such developments can be found in Gustafson and Holloway (1975) and Gustafson et al. (1977). In this paper, we discuss two additional applications: (1) the development of an index of underservice, and (2) a subjective model of demand.

D. A Model of Underservice

The Alcohol, Drug Abuse, and Mental Health Administration (ADAMHA) Workgroup on Epidemiology, Health Systems Research, and Statistics/Data Systems report (1979) that was provided to the participants in this meeting recommended the development of models of "unmet" need. There are several possible approaches to this problem. One could measure underservice through traditional needs assessment methodologies, which generally involve three stages: first, establishing basic epidemiological rates of disorder in the community; second, classifying disorders into homogeneous groups; and finally, identifying the resources necessary to meet those needs. The difference between existing service levels and the predicted needs for services would be the measure of underservice. In our opinion, any attempt to follow this approach closely would encounter several major difficulties. Widespread application would tie up large sums of money in community-based, epidemiologic surveys. Linking specific resources to specific patterns of needs could also be problematic, because, as discussed earlier, opinions regarding the relationships between needs and desired treatments vary in the mental health field. Applying traditional methods of assessing need also could lead to the specification of unrealistically high levels of service. Legislators would surely balk if adequate service levels were defined to be three or four times that of existing budgetary resources.

Subjective probability models could be of great assistance in many stages of this traditional approach to measuring needs and underservice. An alternative approach, however, derived from our experience in the development of an index of medical underservice (Health Services Research Group 1975), should also be considered. In 1974, the Index of Medical Underservice (IMU) was developed in response to a congressional mandate that high priorities for health maintenance organization (HMO) funding be assigned to "medically underserved areas." The assumption was that there would be substantial levels of unmet need in such areas and that, therefore, the Department of Health and Human Services (HHS) should address those unmet needs by encouraging the establishment of new treatment sources there. HEW was given 3 months in which to establish a mechanism for identifying underserved areas. This short time frame significantly limited the development and testing of the model. In particular, it was clearly necessary to rely upon existing and commonly available data sources.

Experience early in the IMU study showed that, although experts agreed in their assessments of relative underservice for actual communities, they simultaneously disagreed on a common definition of underservice. This observation led to the idea of "common wisdom," which subsequently provided the philosophical basis for the IMU. Common wisdom exists if different experts agree on which areas are most underserved. If one accepts the premise of common wisdom, then one simply needs to develop a model that will predict these judgments. There are clear advantages to understanding how and why an area is underserved, but even that research must rely upon a tool that determines the value of the dependent variable, underservice.

Once the concept of common wisdom was accepted, a panel of experts was asked to choose from a list of commonly available variables (beds per 1,000 population, infant mortality rates, average per capita expenditures for health care, etc.) a subset of variables they felt to be indicators of underservice. They mapped the relative importance of each indicator onto a utility function, scaled from zero to 100, and constructed utility curves to describe the relationship between the values of the indicators and the relative degree of underservice. The IMU is simply a weighted average of these utility scores. The IMU was validated by comparing its predictions with the independent assessments of underservice in 62 communities. The model successfully predicted the common wisdom of the panel of experts, was eventually implemented, and continues to serve several programs. Although this model has been criticized, as any index for establishing funding priorities would be, no acceptable alternative has been developed during the 7 years since its creation.

Given this experience, could a similar model be useful to the National Institute of Mental Health (NIMH)? The answer to this question appears to be a cautious "yes." Our uncertainty comes from two sources. First, we do not know if there exists common wisdom as to comparative levels of unmet needs for ADM services. Without common wisdom, this modeling approach could not be employed. Second, the utility of an index of mental health underservice is unclear. The model described here is useful for ranking communities' needs on a national basis. If a prescriptive model were desired, for example, to measure shortages in specific treatment modalities (e.g., outpatient therapists), no single model of underservice would suffice. Rather, several individual models would be required, one for each treatment modality. The MAU model with its quick and easy developmental requirements offers a desirable approach for these individual models just as it did in creating the more global IMU.

E. A Subjective Model of Demand

As we approach the advent of a national health insurance (NHI) system, there remain many unanswered questions regarding the inclusion of mental health benefits in the scope of program benefits. What kinds of services should be covered? How much should the country expect to pay for these services? For any particular package, what will be the effects on existing patterns of utilization? Will there be a shift from public to private sources of service? What cost-containment limits, if any, (e.g., maximum number of visits per year) should be imposed?

A great deal of work has been done trying to find answers to such questions. This work appears to fall into two general categories: (1) empirical studies of existing or past insurance plans and (2) a macrolevel, expert panel study. Each approach suffers from several limitations. Problems in empirical studies include the following: nonrepresentative base populations (e.g., HMO studies); truncated utilization and demand data because of insurance limitations; and possible nonfinancial limitations (e.g., nonavailability of services and other nonfinancial barriers to access). The ADAMHA Workgroup on Cost Estimates, Office of Program Planning and Evaluation (1979), apparently adopted a macrolevel approach to the problem, providing generalized estimates of the impacts of NHI. Edwards (1966) noted, however, that regardless of their expertise, most humans do not make reliable judgments where many factors need consideration. Thus, the validity of the expert panel's opinions may be in doubt.

In our opinion, a marriage of the empirical and the panel studies, using subjective probability models as described in this paper, would reduce the limitations of the two approaches taken separately. First, the expert judgments would be used to address questions on a micro level. Experts could, if provided with relevant background data, suggest adjustments to, or make estimates about, specific empirical utilization rates. For example, they could estimate the relative changes in outpatient utilization resulting from a lower socioeconomic status distribution than that of the population in an empirical study. Thus, the expert judgments would be used directly to address the limits imposed by existing data bases. Using these adjusted estimates, operations researchers could construct a model to aggregate the effects of these adjustments to a national scale; that is, a mental health services demand model could be constructed.

Our experience in the health sector suggests that this approach is feasible and might be successful. In 1978, we studied the effects of three NHI proposals on the rate and cost of services received by patients eligible for support through the Bureau of Community Health Services (BCHS) (Gustafson et al. 1978). Experts were provided with the best utilization data available from multiple data sources. These data were most often irrelevant to the populations served by the BCHS. The expert panels generated utilization curves, adjusting the resultant patterns of demand to reflect the characteristics of the BCHS recipients. A simulation provided national estimates of demands and costs. The model was replicated with empirical data over a 3-year period. (Note that the original study cost about $60,000, while the validation cost over $500,000.) This study presents strong evidence that, if properly approached, subjective probability models, when combined with aggregation models, could provide the NIMH with improved estimates of the impact of NHI proposals on patterns of demand for mental health services.

III. DISTRIBUTIONAL MODELS OF UTILIZATION AND DEMAND

In this section we begin a discussion of the more traditional models of utilization and demand by considering what we call distributional models. This group of models comprises probability models of the consumption of or demand for a single resource by some specified population. Also included within this arbitrarily defined group are distributional models of length of stay (e.g., Eaton and Whitmore 1977), single-resource queuing models (e.g., the infinite channel queue model used by Reuter and Von Korff 1980), and models of distribution of demand (Kessler 1979).

The importance of these models derives from several factors. First, they describe the basic distributions of a large number of utilization variables. Thus they should provide some insight into methods for estimating utilization variables and for making statistical comparisons. Second, these relatively simple models of utilization and demand can provide a basis for valid formulations of more complex models of utilization. Third, the parameters of these models suggest that we may need to review carefully the design of mental health program evaluations. Finally, because these are the simplest models of utilization and demand, it is likely that candidates for immediate implementation will come from this group. Accordingly, it is imperative that both the strengths and the limitations of these models be clearly understood.

A. Current Status of Models

The literature does not identify any single distributional form as a "best" model of length of stay in a mental health treatment system. Indeed, there can be as much disagreement as there is agreement among researchers, even when using the same data base. Fortunately, the patterns of consensus and contention provide some insight into the directions that should be taken in future research and applications.

The existing literature is in agreement on questions relating to the shape of the distributions of service. In particular, the distribution of length of treatment is sharply skewed to the right and has a generally decreasing hazard function. These characteristics are shared by the following theoretical distributions, which are the major contenders for distributional models: the mixed exponential, Weibull, lognormal, and inverse Gaussian distributions. This basic shape appears to be valid across a variety of settings and treatments.

The skewness of these distributions of treatment duration is not surprising; it simply implies that more patients experience short spans of treatment than long ones. This skewness is true of distributions of all types of utilization, including utilization in the health care system. However, it can create some difficulties in accurately estimating treatment patterns. Extremely long durations of care, even though relatively infrequent, can have major effects on estimates of means and variances. The long tails of these distributions also can create sampling problems; that is, unless the observer is willing to wait for a very long time, the sample of cases available for estimating lengths of stay is truncated, or censored, by elimination of the long-stay cases. Thus, cases that could have a major effect on estimates of the parameters of treatment duration are kept from the sample. The use of censored samples can introduce serious biases of underestimation into analyses unless the estimation procedures are adjusted appropriately.

Censoring of samples is a much more severe problem in analyses of the mental health system than it is in the health care system; mean and maximum treatment durations tend to be much larger in the former. The dangers of biased results can be easily avoided if the problem is recognized and proper estimation procedures are used. Gross and Clark (1975) and Von Korff (1979) discuss the use of various estimation procedures for several distributions.

Another characteristic of distributions of utilization that researchers agree upon is a declining hazard function. Three of the four distributions that have been successfully tested as models of utilization (Weibull, mixed exponential, and lognormal) share this characteristic. For readers not familiar with the concept of hazard function, it is simply a function describing the trend of the probability that an event will occur as a function of time. In mental health systems, it is frequently stated that the longer a patient has been in treatment, the more additional treatment that patient will need (no cause-effect relationship implied). For example, the cohort of patients in a hospital for 6 months might have an expected length of additional treatment; this type of increase would characterize a declining hazard function. In effect, a declining hazard function reflects a tendency of mental patients to become patients needing chronic care; that is, to have a declining probability of discharge, the longer they stay in the system. The prevalence of declining hazard functions of utilization raises many significant questions deserving research. For example, are there patient-mix variables that account for this characteristic? Is this shape due to our approach to treatment; that is, are our treatments producing individuals adapted to the patient role as opposed to a more normal lifestyle?

Another point of agreement among investigators is that the exponential distribution, a favorite of operations researchers, is not an acceptable model of treatment duration or length of stay. This negative result holds true across patient types, treatment settings, and administrative policies. The major implication of this finding is that it will eliminate some models from consideration when the discussion moves on to more complex systems models. In particular, it implies that traditional queuing models and Markov processes are, in their usual forms, not good models of utilization because they rely heavily upon the exponential distribution.

Finally, although the point is seldom stated explicitly, researchers seem to share a general sense that there is probably no basic underlying distribution of the utilization of mental health services. Although the general shape of these distributions is consistent, the range of estimated values seems to vary substantially from setting to setting, even when effects due to diagnoses or need are reasonably controlled. Distributions of utilization may be as much a function of public policy, method of financing, and available treatment alternatives as anything else. For example, consider the Wisconsin experience as described by Kaufman and Kraniak (1979). In 1974, the Wisconsin legislature passed a law that in effect reclassified many of the State's county mental hospitals as nursing homes. One side benefit of this action was that these institutions became eligible for Federal Medicaid/Medicare funds for recipients between the ages of 21 and 65. These funds were not available to these homes when they were called psychiatric hospitals. As a result of this legislative change, an estimated 10,310 nursing home beds in Wisconsin are now filled by individuals whose major disability is a serious mental disorder; more than half of these individuals (5,900) reside in nongovernmental (i.e., non-State or non-county-operated) institutions. Although no data have been published spanning this change, the effect on the measured values of inpatient psychiatric utilization in Wisconsin must be large. Because the patterns of utilization and demand are so sensitive to factors other than epidemiologic needs (such as local policy, availability of treatment alternatives, and financing), it is doubtful that these simple models will ever be easily transportable without complete reestimation for every setting.

B. Declining Hazard Function and System Steady State

Although it may appear to be of primary concern to mathematicians, the slope of the hazard function has serious implications for anyone wishing to analyze or evaluate a mental health system. The key factor is that the slope of the hazard function is directly related to the time required for a system to reach a steady state. Given a constant mean duration of treatment, systems whose distributions have hazard functions with a negative slope require much more time to reach a steady state than systems having distributions with either flat or increasing hazard functions. To place this relation within a real-world context, consider the following examples drawn from Reuter and Von Korff (1980). The authors of that study employed a Weibull distribution to model duration of outpatient treatment of schizophrenics whose average treatment duration was 388 days. The slope of the hazard function appeared to be negative. Using this distribution as a starting point, the authors simulated five hypothetical systems. In three cases, average duration was held constant while the slope of the hazard functions was changed (decreasing, constant, and increasing). In two other cases, the hazard function kept its observed negative slope while the average duration of treatment was reduced by 25 percent and by 50 percent.

The results of these simulations clearly document the importance of the slope of the hazard function in determining the time required for the system to achieve equilibrium. The system with the increasing hazard function stabilized in 3 to 5 years. Each of the other cases required between 10 and 25 years to reach a steady state even when the length of stay was sharply reduced.

What are the implications of this result? First, it should be noted that the slope of the hazard function separates the dynamics of patient demand and utilization in acute health care systems from those of mental health delivery systems. Most acute care is time-limited, almost by definition. Thus, the hazard functions of treatment duration increase, and, as a result, general health care systems stabilize relatively quickly. Consider a hospital with an average length of stay of 7 days. If the distribution of stay were changed (e.g., by actions of a professional standards review organization), the effects of this change on the system's production levels (patient census, etc.), would be directly observable within 4 to 6 weeks. In contrast, the ultimate impact of a change in a mental health system might never be directly observable, at least not for many years.

Consider also the implications of a declining hazard function for the design of evaluations. An evaluator may never be able to observe the ultimate impact of a change in policy; too many years must pass before the total effect on demand, utilization, and patient mix is realized. In this situation, how does one measure the costs and effects of a change? Observed costs and benefits will underestimate the eventual effects, that is, the equilibrium effects. On the other hand, given the excessive time necessary to attain steady state, intervening policy changes could affect the eventual outcome. Thus, it could be inappropriate to use predicted equilibrium values as a basis for comparison. Obviously, there are no pat answers to this dilemma. One implication is that evaluators and planners need to consider the condition of the system from which the data are gathered; that is, is the system in equilibrium, or is it in a transitional phase? In the latter case, one must interpret one's findings accordingly.

A second implication is that analysts should develop mechanisms for analyzing systems in transition. One possible approach is to base the analyses on complex systems models of patients' demands and utilization. The development of such models is an area in which operations researchers could play a major role. The actual structure of these models is discussed in the section of this paper on complex systems models.

C. Future Research Needs for Distributional Models of Utilization and Demand

As previously noted, there is probably no single underlying distribution of demand and utilization for mental health services. Too many external factors enter into consideration. Thus, it is reasonable to question the desirability of continuing to support distributional analyses.

In our opinion, there are three reasons for continuing to support these analyses. First, many techniques of statistical analysis rely upon distributional assumptions; for example, regression requires independent, normally distributed errors. Distributions of demand and utilization are sharply skewed and could be problematic for some analyses. Although transformations of data can address these problems, the appropriate transformation is a function of the distributional characteristics; hence the need for improving the state of our knowledge of distributional aspects of demand and utilization. Second, the wide range of distributions of utilization implies that many samples will be censored. Thus, the appropriate calculation of even basic parameters, such as mean treatment duration, requires assumptions about the distributional form. Finally, to determine if a system has stabilized after a change requires knowledge of the characteristics of the distribution of utilization and demand. In conclusion, although more distributional research may not produce any direct benefits, the results of the work should affect how we analyze mental health systems.

With this goal in mind, it is our opinion that NIMH should undertake the development and dissemination of an inventory of mental health services demand and utilization distributions. This inventory would contain the distributional characteristic of demand and utilization for a variety of patient needs across a variety of settings. For example, a two-dimensional matrix of five to ten classes of illness versus an equal number of treatment settings (inpatient, outpatient, HMO, etc.) could be set up to identify gaps in knowledge. It would then be relatively straightforward to go about bridging the gaps with data from appropriate sources. It should be reemphasized that the interest here is in distributional shapes, characteristics, and ranges of values rather than specific parameters. This project could be best completed by NIMH because it has access to the widest variety of data sources. The availability of an information matrix of this type could be a boon to evaluators as well as to planners by helping them to design appropriate studies based upon reasonable expectations and time scales.

As previously suggested, the basic research in the area of distributional models of utilization should be oriented toward bridging gaps in knowledge rather than breaking new ground. There is also need, however, for increasing the use and implementation of these models beyond their use as a foundation for more complex evaluation and planning studies. One possible application comes from Kessler (1979). The goal of this proposal is to provide an estimate of unmet need based on easily observable utilization data. The basic model is provided by compounding a Poisson distribution (the number of visits) with a gamma distribution (the likelihood of seeking care). The resulting distribution of number of visits across the total population needing care is a negative binomial. If this model were judged adequate, it would be possible to estimate the parameters of the negative binomial from the truncated sample of persons who make at least one visit, and then to calculate the number of people who do not seek care. This latter percentage could be interpreted as a proxy measure of the amount of unmet need in the community. The cheap, readily available proxy measure for a complex, difficult-to-measure concept accounts for the desirability of this approach.

Useful as this model might be, there are several validation steps that should be performed before any effort is expended for widespread implementation. First, although the model has been validated in a single setting, it should be tested in many more. The Marshfield Clinic in Marshfield, Wisconsin, where the model was tested initially, presents an atypical case because it is the only significant source of care of any kind in its region. In urban centers, the model might require a different formulation. Obviously, it would be inappropriate to estimate separate models for each institution. This would create more and more unmet need as more institutions contributed their share, whereas the reality could be just the opposite. As an alternative, one could combine the utilization patterns on an area-wide basis to generate a single value, although utilization patterns for different types of institutions in a single geographic area might not be comparable.

It should also be noted that this approach could be dangerous if applied indiscriminately. A simple-minded effort that merely found the distribution that best fit the truncated distribution and then extrapolated it to zero could provide extremely misleading results. For example, ignoring certain technical arguments, suppose that both a lognormal and a mixed exponential distribution have been fitted to the same set of data. The lognormal distribution intersects the origin (zero unmet need), whereas the mixed exponential does not; thus the amount of unmet need derived from each model would be quite different. Further exploration and refinement of this approach is necessary before its utility as a surrogate measure of need and demand can be adequately assessed.

IV. COMPLEX SYSTEMS MODELS

The preceding section presented some models that described consumption rates of a single resource. In this section, we present a series of more sophisticated models for the flow of patients through complex systems of care. This can be accomplished by modeling the consumption of more than one type of resource and by explicitly providing a description of the flow of patients between resources in the model. In theory, such models can also incorporate both sides of the need-utilization boundary.

A. The Case For and Against Complex Models of Mental Health Systems

There are many advantages and disadvantages to the use and development of complex systems models. The most obvious advantage is that these models allow one to perform analyses that would be extremely difficult to accomplish in any other way. A system is by definition a collection of interacting parts; an analysis of a system must be concerned, to some extent, with the interaction of these parts. The subjective probability and utility models described earlier assume that these interactions are contained implicitly within the experts' judgments. The distributional models considered only the demand and utilization of a single resource. With complex models, one can consider the interactions of many resources and the effects of factors in the system's environment (such as changing levels of need) on the performance of the system. Theoretically, one could combine variables relating levels of need, manpower, resources, effectiveness, and utilization rates into a single, global model of a mental health system (see, for example, Tilquin 1976).

The second primary advantage of using complex models derives from the modeling process. The specification of a model, whether or not its parameters are ever estimated with data, forces administrators and decisionmakers to specify the system under consideration. In this sense, the modeling process is analogous to the development of a computerized information system. The modeler must specify all elements of the system, the exact function of each element, the interactions of the subsystems, and the ways in which factors external to the system influence its internal behavior.

This requirement for detailed definition can raise serious problems of causality. We do not know how the mental health system functions on a detailed level. In fact, this uncertainty is one area in which one would hope a system model might help. But how can it help when what we need to know is precisely that which we need to construct the model? The resolution of this dilemma lies in the fact that a model is a dynamic construct. The modeling process begins with a conceptual structure representing what we think we know about the system. Data are then used to test various aspects of the model. This process also identifies areas where new data are required. Thus, the basic conceptual model acts as a guide for research needs. The modeling process can be seen as an iterative loop. During each cycle of the model's development, both our knowledge about the system and our ability to analyze the system increase.

One practical limitation to this iterative process is that any development or application of models of complex systems requires a delicate balancing of desirable but conflicting characteristics. If the model is realistic and detailed in one setting, it is probably not very generalizable. If the model emphasizes mathematical rigor, then either one will have to give in on some level of detail and make additional simplifying assumptions (reducing the model's correspondence to the real world), or one will have to build in sufficient detail that the quality of supporting data sets becomes a limiting factor. The availability of data sets also becomes a problem if one wants to exploit the capability of these models in multiprovider systems. Operations researchers refer to this balancing of limitations as the art of modeling, but it is imperative that the user of the model also be cognizant of the trade-offs involved and the assumptions being made.

The major barrier to the actual development and estimation of complex models of mental health systems is the problem of defining the system and its components. Let us begin by considering the concept of states. Nearly all models embody this concept in one guise or another. Network models designate states to be specific resources, organizations, or referral points across a system (Burgess et al. 1974). Some Markov models define states to be resources

(Reuter 1977) and patients' conditions (Thomas 1968; Marshall and Goldhammer 1955). Simulation models have used an extremely wide range of factors to define their states. At least one proposal for a global model of a health care system carries the definition of states to extreme lengths, including states for each diagnostic group, for varying levels of physician information, for resources, and even for patients' changing perceptions of their problems. The basic concept of a set of states clearly is flexible. Although such an inclusive approach to models is possible, at least two factors limit the ways in which we can use this basic building block. The first relates to problems in definition, and the second involves a restriction due to existing data bases.

Because states and their behavior represent the basic units of analysis in any complex model, the definitions for any set of states should be globally exhaustive across the span of interest. Individual states should be uniquely defined and mutually exclusive. In a patient-flow model, for example, each individual in the system would have to be assigned to only one state at any given time. Any attempt to model mental health needs obviously must sacrifice the requirement for uniqueness of definition, because the number of states required to span the entire range of patterns of needs can be great. With currently available samples, the result would not be a model but a collection of case histories.

Given the difficulties of describing needs as states, it becomes obvious why there are so few models that bridge the need, demand, and utilization examine boundaries or changing levels of need. The definitional problems are currently overwhelming. The few models that do incorporate some measure of need are usually estimated for well-defined conditions. For example, Bernard et al. (1977) model a system for mentally deficient children; Von Korff (1978) examines the dynamics of treated prevalence rates for schizophrenics. Even these examples are not true models of changing needs; rather, the needs of each individual stay relatively constant while he or she moves into and out of treatment.

A second definitional problem arises from the fuzzy boundaries of mental health systems. Some non-mental-health agencies, such as law enforcement and social welfare agencies, provide significant amounts of care for the mentally disabled. Mental health agencies, such as outreach programs, perform social welfare tasks. Including these factors explicitly in a model can be extremely difficult.

A final definitional problem relates to the specification of the product of mental health systems. Treatment outcome represents one possible product, but, as noted earlier, this remains a judgmental concept. Because units of service are easily identified, many researchers have taken a process approach to mental health systems modeling. However, these utilization models fail to address the purpose that the product serves; that is, they do not link services to need, demand, or outcome. Much work clearly is needed in defining the products of the mental health system if systems models are to make substantial contributions.

The definitional problems referred to above are of primary concern during the conceptualization of a mental health system model. There are also significant problems related to the task of fitting data to the conceptual model. First, few data bases are collected for entire systems of care. The only exceptions known to us are the Maryland Psychiatric Case Register, which is no longer operative, and the Multi-State Information System operated by the Rockland State Hospital in New York. The latter system is not totally comprehensive, because it does not include data on the private sector and, for some States, does not include outpatient services data. Although the system has the capability to collect outpatient data, it is not always used. The Case Register is limited by the range of variables it collected, and it is no longer current.

Across most other systems, data collection is extremely fragmented. For example, an individual could have an acute psychotic breakdown resulting in admission to a nursing home, acute-care general hospital, or psychiatric hospital. Medicare, Medicaid, or a private insurance carrier might be the only agency outside the care-providing institution with this information. If the benefits run out under one carrier, then one of the other carriers would pick up the monetary responsibility along with the relevant data. Moreover, these insurers might provide only partial coverage. While a local or county mental health agency or a community mental health center provides psychiatric or after-care benefits in a case like this, it is probable that no single agency would have data describing the entire episode of care.

The sad fact is that data bases are designed around funding sources, or financial institutions, not around treatment systems above the institutional level. Thus, unless a special effort is initiated to gather data from these separate sources, it will be impossible to support an effort to estimate a broad-scope, data-oriented model of a mental health system. Models of specific institutions, individual programs, and categorical programs (such as drug abuse programs) may be possible. Only those models that truly attempt to integrate the potpourri of mental health programs into a system are unsupportable due to data limitations; unfortunately, they may be the most interesting.

A second difficulty that stems from the design of current data bases is the lack of uniform definitions between data bases. For example, the scope of benefits provided by an agency differs from place to place. Thus, the scope of the system that would be included in a data base would differ from place to place. In a more direct manner, terminology varies substantially across settings. For example, whether a particular service is an admission to a skilled nursing facility, an intermediate-care facility for the mentally retarded, or psychiatric hospital may depend more upon local policy decisions than upon real differences among these services. What might be marriage counseling in one setting could be couple therapy in another and family therapy in a third. Thus, lack of uniformity can be a barrier to efforts to combine data bases to support larger, more comprehensive models.

B. Current Applications

The simplest of all complex systems models are network models. These models can provide a basic description of a mental health system, and they do not require a great deal of technical skill to develop, implement, or understand. In their most basic form, network models are composed of two elements: nodes (or states) and arcs connecting the nodes. These models are most commonly used as simple models of patient flow. In this type of application, the nodes represent various resources or agencies with a service delivery system, and the arcs describe the flow of patients between the nodes.

Using the basic building blocks of nodes and arcs, network models can address two questions. First, they can be used to describe the network of referral paths within a system. This was the goal of Burgess et al. (1974) when they developed a network model of a treatment system. In this application, the authors identified the referral paths through a system, placing special emphasis upon the possibility of cycling between nodes. It was suggested that cycling was bad and that, therefore, the presence of cycles could be used as a simple evaluation measure indicative of poor performance. Although we do not know many of the specifics of that particular situation, we do know that cycling through an agency is not always a bad thing. In some situations cycling is considered to be desirable. For example, many State hospital systems have tried to adopt an easy-in, easy-out policy for patients to discourage the use of State hospitals as caretakers of chronic patients. Thus, although cycling may be a useful concept in specific settings, it would be difficult to view it as a major evaluation tool.

A second application based upon network models is the development of models of patient paths by means of a simple extension of the preceding model. This application begins with the identification of each node. Then, by using a data base that tracks patients over time through the various nodes, a researcher can enumerate a set of routes through the system. There are several variations on this basic theme. First, different sets of paths can be developed for patients with specific needs. A second variation involves changing the criteria used to define the nodes. For example, types of therapy could be used to define the nodes. A network model based on therapies would be used to establish the required capacity for each type of service throughout an entire system; these capacities could then be apportioned across the various agencies in the system.

In addition to network models, Markov models have also been used to model complex systems. Here we include traditional Markov chains and processes as well as the more sophisticated semi-Markov chains. These models are stochastic models of the changing state of a system over time. They can be used in a variety of ways. In theory, one could specify a model composed of states representing a patient's condition and the probability of changes in that condition. In health and mental health systems, these models are sometimes used as population models depicting the flow of patients through a treatment system.

Markov models provide several benefits in describing patient flow. First, they are relatively compact models. Whereas a long string of referrals can overwhelm network models, Markov models fold these strings into a transition matrix. Therefore, this approach can result in a much smaller and more easily comprehended model of extended episodes. Also, the transition matrix, subject to homogeneity restrictions, can represent many different paths in one model, unlike network tracking models, which describe each path separately.

A second advantage of Markov models is that they are analytic models. They can be easily used to predict the future state of the system, patient flow between states, the expected patient census within states, etc. Thus, they can be used to analyze systems in transition when the utilization distributions have declining hazard functions.

A third advantage of Markov models is that they are conceptually straightforward. Administrators of health and mental health systems conceptualize patient flow in terms parallel to the components of these models. For example, Markov models use a transition matrix analogous to a referral matrix. Administrators frequently think in terms of length of stay in treatment units. Semi-Markov models have what is called a matrix of holding time distributions; this is little more than a matrix of length of stay distributions. Thus, although these models may be computationally beyond the average administrator, the conceptual fit of these models to preexisting patterns of thinking could favorably affect the acceptability of results derived from them.

There have been at least two types of applications of Markov models in health and mental health systems: institutional models and population models. The institutional model (see, for example, Kao 1974 or Reuter 1977) provides a description of patient flow through the treatment units of a complex institution. Typically, this model is based on the structure of an absorbing Markov chain. The model becomes "aware" of the patients as they enter treatment and ceases tracking them when they are discharged (i.e., absorbed).

The major failure of these models is their inability to incorporate the effects of a heterogeneous population within the boundaries of the system being modeled. They can model the impact of population characteristics as individuals initially cross the system's boundary. For example, Reuter (1977) uses regression equations to predict the entry portal of patients. However, once the patient crosses into the system, the model necessarily treats the population in each state as homogeneous. A small degree of heterogeneity can be successfully modeled by splitting the states within the model. Reuter was able to validate his model after a twofold increase in the number of states (12 treatment units became 24 states); this approach obviously has its own computational limitations. The evidence suggests, however, that Markov models of patient flow within institutions can be successfully estimated and validated.

True populations models are a second type of application of Markov models in health and mental health systems. These are not absorbing models, but include the flow of individuals into and out of treatment. They are characterized by several states for untreated populations (e.g., well, ill but not treated, etc.) in addition to one or more treatment states. Thus, these models do span the need, demand, and utilization boundaries. Examples of this approach include Marshall and Goldhammer (1955) and Von Korff (1978). The major limitation of these applications is the requirement that the population being modeled must be homogeneous with respect to the model's parameters. The effect of this restriction is to limit these applications to well-defined populations (for example, Von Korff's model is limited to schizophrenic patients).

Although these models are limited in their scope, they can make a significant contribution to our understanding of prevalence rates. Currently, the only reasonably inexpensive method of estimating the prevalence of mental disorders is to rely upon figures for the treated prevalence.

The models described here provide a basic structure for research in the dynamics of the relationship between treated and pure prevalence rates, that is, between prevalence of certain treatments and prevalence of certain mental disorders. Thus, although these models do not explicitly contain factors related to changing levels of need, they do allow us to predict how changing needs would affect the size of treated populations.

A third type of model that can be used to investigate complex systems is the digital simulation model. Digital simulation models represent the ultimate in flexibility. Only the researcher's imagination and budget limit the range of concepts and relationships that can be included within a single simulation model. Despite this freedom, most simulations are built upon the readily available conceptual structures provided by network, Markov, and queuing models. This, no doubt, partially results from the ready availability of simulation languages based upon those conceptual structures. Digital simulations can easily estimate the flow of patients through a complex system of queues. Also, simulations frequently use patient-path data from network models as input to a model of a facility. The derivative structure of most simulation models should not be construed as a denigration of their value. Indeed, even when it is designed upon an existing structure, a simulation approach frequently is the only way to get the desired results.

Digital computer simulation is one of the most frequently used techniques for analyzing health care and hospital systems. Shuman et al. (1975) list 200 citations in the section on simulation. Most of these examples concern investigations of the operating characteristics of hospital subsystems (e.g., blood banks, operating suites, admission scheduling, etc.). Significantly, there is only a single citation for a simulation of a mental health system (Horvath 1971); that paper proposes the development of a mental health planning simulation. Simulation techniques clearly have been underutilized by mental health administrators.

Computer simulations have several disadvantages. First, simulations can be extremely expensive. The cost of simulations can increase exponentially as additional detail is built into the model. Second, simulations can be very difficult to validate. Although validation is a problem with all models, simulations seem to rely more upon face validity than do other types of models.

Third, the previously discussed restrictions imposed by data base limitations also apply to simulations, but this limitation can be more frustrating with simulations than with other models. The data, if available, could improve and validate a simulation; the same is not always true of other models (Markov models, in particular). Finally, simulations are usually situation-specific. We are not aware of a single simulation study that has been used in more than one setting. Perhaps the freedom that allows one to include detailed elements in a simulation model results in limited applicability. This lack of generalizability should be a serious consideration when evaluating the cost-benefit of a simulation effort.

The fourth and final methodology we will consider as a possible model of a mental health system is the dynamic simulation technique. This technique has been used to investigate some extremely complex issues in mental health systems and, therefore, deserves serious consideration. Problems that have been studied using this methodology include the analysis of the dropout phenomenon (Levin and Roberts 1976), a study of rates of mental hospitalization (Hertzman and Levin 1974a, 1974b), and a study of the system of care for mentally deficient children (Bernard et al. 1977). The latter two models were validated.

We are not sufficiently competent in this area to be able to evaluate the structure of these models critically. For interested parties, we recommend the brief description of these techniques provided by Sheldon (1975). We note, however, the desirable attributes of these models. First, results from these models appear to be insensitive to input data. This is a valuable characteristic in the mental health arena, where we are plagued with fragmented data and imprecise definitions. Second, the development of these models places considerable emphasis upon the development of a conceptual model. Thus, they force attention to issues of definition and scope.

C. Projects for Research with Complex Systems Models

There are a large number of projects that, if completed, would make valuable contributions to the field of mental health systems analysis. For expository convenience, they are categorized into two general groups. The projects in the first group are complex models of utilization. The second group consists of models with a broader scope but that will require much more conceptual work before they produce any direct benefits.

Given the current state of modeling technology, it is possible to develop and estimate complex models of utilization. These models could take a variety of forms: networks, Markov chains, or computer simulations. The scope and level of detail of these models are limited only by the data bases required to estimate them. These models could serve a variety of purposes.

First, they could be used to support more sophisticated planning methodologies. For example, from the results of the distributional models and other evidence, we know that mental health utilization rates reflect a dynamic process over time. Also, levels of utilization are sensitive to external factors (e.g., changing scope of insurance benefits). Under these conditions, simple statistical projections are inappropriate. Alternative methods, such as Markov models, could improve our capabilities to accurately forecast mental health service capacities. A second use of complex models of utilization is in program evaluations. Because mental health delivery systems are in transition, complex models could provide better estimates of baseline utilization levels than are available through traditional statistical methodologies.

A review of models and available data makes it clear that any immediate work with complex models will be in the area of utilization models. However, the major advantage of complex models is their capacity to describe all aspects of a system, including changing levels of need, demand, and outcome as well as utilization. The limit on current applications reflects our inability to define the roles, products, and interrelationships among the various elements of the mental health system. Thus, a significant expansion of the utility of complex systems models will require a great deal of basic conceptual development, improvement in definitions, and specification of system elements and functions. Some of this work can evolve without recourse to any specific model. For example, the subjective models described in the second section of this paper could be used to specify basic linkages between need, treatment, and outcome.

Another approach is based upon the use of an interactive statistical package, called AUTOGRP, to develop clusters of patients. This program has been successfully used in health care systems research to identify groups (called diagnostic-related groups, or DRGs) of patients who have similar needs and similar patterns of care. The DRGs are currently being tested as a basis for a prospective reimbursement system in New Jersey (see Fetter et al. 1977 for a more complete description of this project). We understand that AUTOGRP has already been tested at least once in a mental health setting, but we are not aware that any results of that effort are available. Even if that project was a failure, however, a careful review of it might provide guidelines for developing future strategies.

An alternative strategy for research is to emphasize the development of a conceptual model of the mental health system. This model would then serve as a tool for identifying gaps in knowledge and data bases. For example, one could begin by developing a complete specification of the mental health system. If we are ever to be successful with systems efforts, we need a basic description of the system in which we are working. Whether we work at the macrosystem level or simply develop models of small subsystems, a key factor for success will be a clear understanding of the role and function of the entity being modeled and its relationship to its immediate environment.

We therefore propose the creation of a conceptual model of this sort. The working hypothesis of this study is that there is a mental health system that has boundaries and identifiable subsystems. To describe them would be the goal of the project. Operational tasks would involve development of several network models of the mental health system. Each model would be used to define a specific dimension of interagency relationships. For example, one model would represent a referral network of patients. A second model would describe the flow of resources (money). A third network would describe licensing and certification authority; a fourth could depict lines for accountability for quality. Several models could be developed to describe the agencies with responsibilities for services to specific types of patients.

This study would provide several direct benefits. First, it would identify those portions of the mental health system least integrated into the total system. Second, it would identify existing mismatches between lines of accountability and control. Third, it would identify agencies subject to multiple and, therefore, possibly conflicting lines of control. Fourth, it would identify those categories of patients for whom mental health care is spread among multiple agencies.

Beyond these direct benefits, the most significant value of this work would be to identify future areas for model development. Subsystems that have well-defined lines of responsibility, function, control, and patient flow would be identified. These subsystems could then be singled out as opportunities for the development of true systems models. Thus, the network model could serve as the first step in the iterative process that will eventually lead to the use of more data-oriented systems models. Until this conceptual groundwork is completed, however, the real promise of complex systems models will remain total system. Second, it would identify existing mismatches between lines of accountability and control. Third, it would identify agencies subject to multiple and, therefore, possibly conflicting lines of control. Fourth, it would identify those categories of patients for whom mental health care is spread among multiple agencies.

Beyond these direct benefits, the most significant value of this work would be to identify future areas for model development. Subsystems that have well-defined lines of responsibility, function, control, and patient flow would be identified. These subsystems could then be singled out as opportunities for the development of true systems models. Thus, the network model could serve as the first step in the iterative process that will eventually lead to the use of more data-oriented systems models. Until this conceptual groundwork is completed, however, the real promise of complex systems models will remain unrealized. In summary, we have the technical tools available. Application of these techniques must await the basic groundwork of definition and specification.

V. CONCLUSIONS

In this paper, we have attempted to define some of the capabilities and limitations of the use of systems models of mental health systems. Consistent with the charge given us as members of this ad hoc advisory group to NIMH, we restricted our attention to descriptive models of need, demand, and utilization. As should be evident from our discussion, many possible uses of these models can help in addressing problems currently faced by NIMH. To a large extent, the technology exists and awaits the specification of appropriate problems. We have, therefore, specified four specific problem areas in which operations research and systems analysis could be applied now. These are:

1. Development of an index of underservice for mental health services;

2. Development of a mental health demand simulation model for use in evaluating national health insurance proposals and their impact on the mental health system;

3. Development of an inventory of distributions of mental health services utilization for use in planning and evaluation studies; and

4. Development of a descriptive network model of the mental health system and its components.

One limitation of our presentation is an overemphasis on models. Systems analysis and operations research are as much a state of mind as they are a collection of techniques and methodologies. As noted by Dr. L. Shuman, University of Pittsburgh, "Although OR originally began as a multidisciplinary, interdisciplinary approach to problem solving, as it has become a legitimate academic discipline, the multidisciplinary emphasis has often been obscured." Surely, the interest voiced by the ADAMHA workgroup in the systems approach to the mental health system was not a call for the development of models; rather, it was a call for the development of a rational, unified, and systematic approach to the analysis of the mental health system.

One method for achieving this is through the development and use of systems models. As noted, however, the mental health system is not ready for the application of these complex models. This lack of readiness is a direct result of the lack of a systems conceptualization of mental health care delivery systems. The key factor here returns us to the iterative nature of systems models: First we conceptualize and define, then we fit data and test the conceptualization. We adjust the model, redefine, retest, and so forth. Thus, before systems models can be used, we must learn to express our problems and goals within the context of a system. There is little point in developing models if the questions are not properly formulated.

With this perspective, it should be clear that operations researchers must play a much larger role than merely modeling the mental health system. The most effective use of operations researchers at this stage will be as key members of interdisciplinary teams. The teams should include sociologists, administrators, mental health clinicians, and operations researchers. These teams must operate in the field, actually carrying out the research, and in the highest levels of governments where research and policy strategies are developed. Teams in the field might actually use some of the modeling techniques described herein. Teams in government would serve to insure that the questions asked make sense within a systems perspective. This group would first have to develop a basic conceptual model of the system, and then establish priorities for bridging the gaps. It is only through a careful phrasing of issues and goals within a systems perspective that the presumed value of a systems approach will be attained.

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Chapter 2.

STOCHASTIC MODELS IN MENTAL HEALTH EVALUATION RESEARCH

Richard H. Shachtman, Ph.D., and Eric J. Feuer, M.S.*

I. INTRODUCTION

The purpose of this paper is to indicate desiderata for the application of a certain class of operations research (OR) models known as stochastic models to mental health program evaluation (MHPE). Specifically, we will critique the ways in which a stochastic model might be used for MHPE, including several important and researchable problems in implementing such models. It is not our intention to ignore or demean other OR approaches, such as network theory, simulation, or systems dynamics. We concentrate on one we believe can be applied to and encompass broad aspects of MHPE. Moreover, we believe that the very process of preparing to create such models will lead to successful evaluation approaches whether the output includes a formal model or not.

This paper is directed generally at a non-operations-research reader. We ask this reader's forbearance as we set the framework for our approach so that he or she may critique the potential usefulness and pitfalls of stochastic modeling applications to MHPE. In figure 1 we indicate the triangle of communication necessary for the actual implementation of stochastic modeling techniques in a specific health service agency. Our discussion concentrates on the lines of communication emanating from (A) (see figure 1). We encourage and depend on communication with clinical staffs (B) to help solve the problems of defining appropriate measures for program performance and patient functioning. We encourage and depend on communication with mental health administrators (C) to help set specific program objectives, evaluate the feasibility of measures, and solve the problems of data acquisition and storage.

This paper's concentration on criteria and problems in applying stochastic models is intended to build quickly from a general framework to special problems for MHPE. We briefly review points on experiments and quasi-experiments (section II). After outlining the general approach to stochastic model building in section III, we discuss briefly in section IV evaluative measures and a few stochastic models for MHPE in the literature before proceeding to the longer section V on the implementation of stochastic models. We present our recommendations in section VI.

II. EXPERIMENTAL AND QUASI-EXPERIMENTAL DESIGN IN EVALUATION

The fundamentals of classical experimental design (Cochran and Cox 1950), laid down by Sir Ronald Fisher in the early part of this century, were

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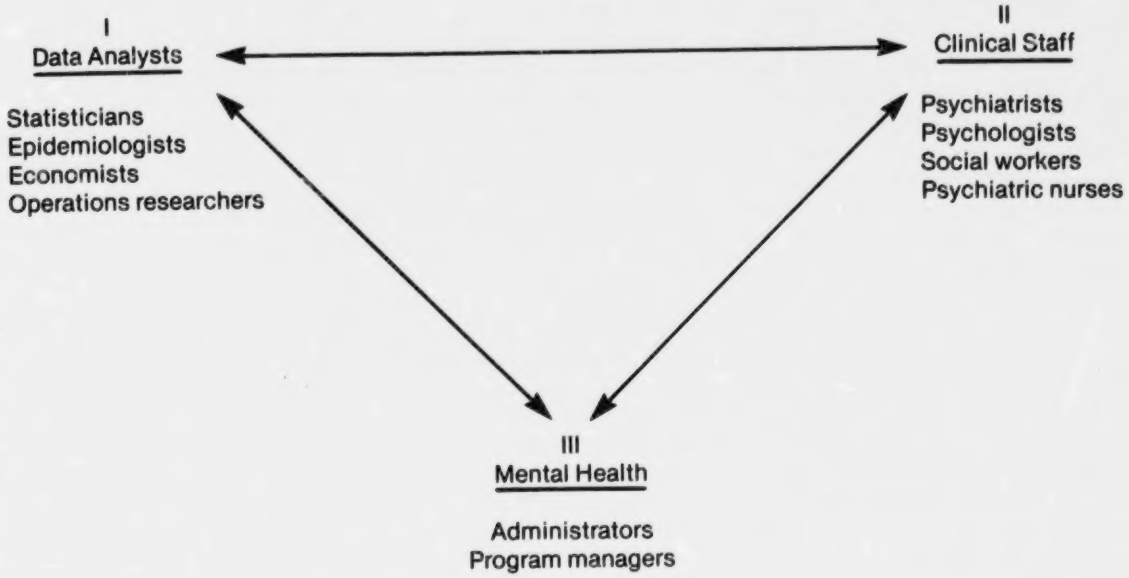
FIGURE 1


I
Data Analysts
Statisticians
Epidemiologists
Economists
Operations researchers
II
Clinical Staff
Psychiatrists
Psychologists
Social workers
Psychiatric nurses
III
Mental Health
Administrators
Program managers

Communication for modeling in mental health program evaluation

formulated to solve problems in agricultural experimentation and industrial quality control. In the early 1950s, the discovery of the psychotropic action of certain drugs in the care of mental disorders opened the door for clinical trials and, later, evaluation studies in mental health (Cole and Gerard 1959). The classical designs were naturally and quickly accepted for these applications; however, many investigators feel that these models of experimental design, which worked well in agricultural experimentation and industrial quality control, do not meet the research needs of clinical psychology and psychiatry. Rather, it is through the "development and application of more dynamic statistical systems and design concepts" (Chassan 1957) that these requirements can be fulfilled.

The standard classical design used in evaluation studies is the analysis of covariance (ANOCOVA) with randomized treatment assignment. This design uses a post-treatment score, such as a clinical assessment on a standardized scale, as a dependent variable to test whether two or more treatments differ significantly after adjusting for the pre-treatment score and other possible confounding covariates. The basic problem with this design in mental health applications is that two fixed-point observations (pre- and post-treatment scores) are insufficient to measure the dynamics of the mental processes of a person or group. The key is that we do not want to measure only the change in a fixed score or value representing the mental condition of a person, but the changing patterns of change. To accomplish this, we must use sequences of observations instead of single fixed-point observations.

ANOCOVA is still commonly used in quasi-experimental designs*, although there must be safeguards against threats to internal validity that result from the lack of randomization into treatment groups. Researchers often use this type of design when evaluating competing programs, because ethical considerations and informed-consent requirements may preclude randomization into programs not equally applicable to all subjects. This lack of randomization into programs may cause biases resulting from (1) differential selection of respondents for the comparison groups, and (2) interaction effects of selection biases and the experimental variable (post-score), causing what is termed the initial group difference problem (Campbell and Stanley 1966). These biases violate an assumption of ANOCOVA in that we are not comparing groups that were initially comparable.

Sometimes matching is used to pair comparable individuals on the pre-score as well as other relevant covariables, and individuals who cannot be adequately paired are removed from the analysis. Because subjects within a particular program interact, however, subjects excluded from the analysis can still affect the outcome measurements of those remaining in it. For example, suppose we compare two classroom programs for the mentally retarded, in which the subjects could not be randomized because the two school programs are aimed at slightly different, although overlapping, initial ability levels. The experiment's purpose is to compare improvement in students' abilities in the two programs. To make the groups comparable, we match the students with the highest ability in the lower group, with those of lowest initial ability level in the higher group (figure 2). It is not inconceivable that the lower ability of the unmatched students in the first group would slow the progress of those matched in this group, while the higher ability levels of the unmatched students in the second group might hasten the progress of the others in their group. That is, the observations are not independent and the nature of the patient mix affects the outcome. The net effect of these biases might cause us to conclude incorrectly that it is the teaching program itself that is causing the matched students in group 2 to improve more than the matched students in group 1, while it is actually the differential patient mix.

Thus, the mental health researcher has the task of developing analytic tools that take into consideration the problems of confounding effects, the nonindependence of observations, and, perhaps most important, the need to reflect change patterns.

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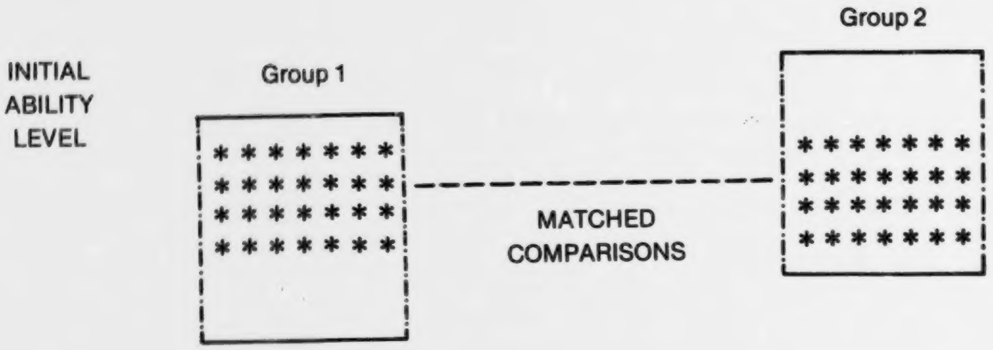
*Quasi-experimental design is used "in many natural social settings in which the research person can introduce something like experimental design into his scheduling of experimental stimuli (the when and to whom of exposure and the ability to randomize exposures) which makes a true experiment possible." (Campbell and Stanley 1966).

FIGURE 2



Comparison of two groups of mentally retarded students with overlapping ability levels

III. STOCHASTIC MODELS

A stochastic model is a mathematical, and sometimes computer-based, representation of sequences of probabilistic events over time, that is, it is an abstraction of empirical phenomena and is useful for description, predicting outcomes, making statistical inferences, and testing the effects of changes in, and to, the process. Thus, such models may be used to compare and evaluate alternative interventions and decisions. Different types of stochastic models use different definitions of events occurring during the process and of the time interval in which they occur. One basic dichotomy is between models that use continuous versus discrete events and time parameters.

One class of stochastic models is known as Markov chains (MCs). For these models one assumes that the probability of the next transition (between states or within a state) depends on only the current state and not on prior ones (Feller 1968). A more general class of models--known as semi-Markov processes--allows more flexibility in the modeling of holding times in states. (See step 8, below.) At the end of this section, we give an example of an MC model for anxiety and depression patterns. In subsequent sections, we review several MC examples for MHPE.

As a prologue, we suggest nine basic steps in constructing a stochastic model aimed toward the derivation of Markov or semi-Markov processes (Shachtman and Hogue 1976; Kastner et al. 1979). Although these points may be evident to the experienced OR analyst, a surprising number of papers do not follow the stages or utilize the statistical tests available for testing the concomitant assumptions. This section provides a brief definition and overview of these steps, while section V considers the special problems inherent in their application to mental health evaluation.

The steps in constructing a stochastic model are as follows:

1. Determine homogeneous subgroups of the sampled population for baseline and comparison analyses.

To perform a stochastic analysis, we must split the sampled group into homogeneous subgroups with respect to characteristics related to the dependent (event) variable. This is extremely important to the mental health modeling process and will be discussed in detail later.

2. Characterize the type and extent of events missing from individual and group observations and examine other data problems.

Although the steps we outline here are in a specific order, they may require feedback from and iteration with other steps. These requirements obtain more frequently when data are missing from each path observation (e.g., missing community mental health center visit information or outside community support program information on a patient) or when data come only in some aggregate form. The latter situation may occur if, for example, we know only the proportion of patients to visit a state. We elaborate on this problem in section V.

3. Develop the structure of state definitions for particular subgroups.

"State space" measures the dependent (event) variable over time. Some stochastic models use a discrete state space to characterize such variables as the location of a psychiatric patient--for example, hospitalized or unhospitalized (Marshall and Goldhammer 1955), or a scale of discrete measures of psychological well-being (Rodda et al. 1971). Other models might employ a continuous state space to measure a cardinal scale of psychological well-being (Whitmore and Neufelot 1970). Although the discrete state space is appropriate for many health service applications, the exact nature of the states used is intimately tied to other considerations of the modeling process. (See section V.E.3.)

4. Select a discrete or continuous time parameter and either an appropriate time interval or intensity function.

A continuous time parameter is the most natural choice for interpretation, although the modeling process and statistical estimation simplify if we restrict transitions among states to discrete intervals. The discrete time reference frame chosen must be short enough so that multiple transitions do not occur in one time interval and long enough so that the Markov property (see step 7) is not severely violated. For acute psychological states, a natural break might be a day, week, or month, depending on the nature of the psychological variable. In mental deficiencies with long latent times or remission and relapse sequences, time intervals may be a year or more.

Most models allow consecutive stays in a state. Many practical situations dictate that a particular time frame be chosen on the basis of available data. The interpretation of results, especially by program managers, of discrete time stochastic processes will probably be easier than working with an intensity function required by a continuous time parameter stochastic process. A reason for using a continuous time parameter is to save computation costs. We know of mental health as well as other health services examples in which working with a continuous time parameter does not seem an insurmountable problem.

5. Estimate transition probabilities and standard errors.

A Markov chain is a discrete-event, discrete-time, stochastic process. This model is often the most practical for simple modeling considerations, although the discrete-time semi-Markov process may be very useful (see step 8).

The definition of Markov chain given above (the probability of the next transition depends only on the present state) is called first-order Markov dependence. In figure 3, we display this dependence in a model for a three-state MC as a transition probability matrix.

FIGURE 3

STATE WILL ENTER NEXT
(State J)

$$\begin{array}{rlccc} & & 1 & 2 & 3 \\ \text{STATE} & 1: & p(1,1) & p(1,2) & p(1,3): \\ \text{PRESENTLY} & 2: & p(2,1) & p(2,2) & p(2,3): \\ \text{IN} & 3: & p(3,1) & p(3,2) & p(3,3): \\ \text{(State I)} & & & & \end{array}$$

First-order Markov dependence in a three-state Markov chain

The element p(I,J) represents the probability of going from state I to state J; I,J = 1,2,3. To estimate each p(I,J) in the matrix, one sums the number of times a subject goes from state I to state J, n(I,J), and divides the sum by the number of times a subject leaves state I, n(I,.). Then p(I,J) is defined to be n(I,J)/(I,.).

Once we estimate a transition probability matrix, we may employ a wealth of analytical results for estimation and hypothesis testing of movement among the states of the MC. From a first-order MC, analytical results permit the computation of the standard errors of the transition probabilities, the expected time to return to a state, the probability of going from state I to state J in time N (N-step transition probabilities), the probability of being "absorbed" in a state from which there is no exit (e.g., death, discharge), the mean time to absorption, and so forth. Anderson and Goodman (1957) and Kullback et al. (1962) present procedures for statistical inference Markov chains. Such tests permit determination of the degree to which a transititon matrix differs significantly from a specified matrix and of the homogeneity of several realizations of an MC. Thus, these results yield inferential techniques to capture changing patterns of change in the subject population.

There are, however, serious gaps in our analytical knowledge. For example, as far as we are aware, there is no closed-form, direct analytic technique for calculating standard errors of N-step transition probabilities. We have developed a simulation technique for estimating these standard errors and applying them to health program data, and it may be used for mental health program evaluation (Schoenfelder et al. 1980). Standard errors are at least as important here as they are in any type of statistical work, especially for establishing confidence limits around transition probabilities that have direct programmatic interpretations. Unfortunately, standard errors are rarely reported.

6. Test time homogeneity (stationarity).

The assumption of time homogeneity requires that, as subjects mature, their transition probabilities do not change. This can be tested by splitting the path codes (i.e., the sequence of states that a subject occupies) at various intervals and testing the homogeneity of the matrices estimated from the subgroups as indicated in step 5. For example, suppose subject path codes (sequences visited in time order) run for 3 years. We can test the time homogeneity by estimating a transition matrix based entirely on first-year data, second-year data, and third-year data, and then testing to determine the extent to which these transition matrices differ significantly.

The assumption may be violated by the very mental health processes that we wish to evaluate. We present suggestions for handling mental health processes in section V.C.2.

7. Test the order of the Markov property.

First-order Markov dependence may not hold for a particular empirical process that may satisfy a more general Nth-order Markov dependence. This occurs when the probability that one subject next enters a certain state depends on the sequence of the last N states. To reflect Nth-order Markov dependence requires an N+1 dimensional transition matrix. The data requirements and possibly the computational effort for even a moderate N clearly preclude estimation of higher order matrices. Anderson and Goodman (1957) and Kullback et al. (1962) provide tests that determine whether the data come from a chain of a specified order. One may frequently capture the order properties by expanding to a first-order MC with many more states. Some states in the expanded process may reflect a sequence of states in the original Nth-order MC. Health service examples occur in Thomas (1968) and in Shachtman and Hogue (1976).

8. Determine the length of stay (holding time distribution) for each state.

An implicit assumption of first-order Markov dependence is that the length of stay in a state is geometrically distributed. This distribution characterizes the probabilities of waiting in a state. At each time period, the process may stay in the state with a probability of q or leave the state with a probability of p, where $p + q=1$. The probability of leaving after exactly n time periods is then $q^n p$, $n=0,1,\ldots$.

If the assumption of a geometric distribution for length of stay cannot be met, then the empirical process should be modeled as a semi-Markov process. In this case, it is necessary to calculate frequency distributions of length of stay (holding time distributions) in each state. For computational efficiency, the analyst often fits a well-known probability distribution to the observed frequency distribution for holding time and estimates parameters so that all manipulation can be accomplished with fixed, well-known analytic distributions. Mixtures of geometric distributions frequently are used for the discrete case, and mixtures of exponential distributions frequently are used for the continuous case.

9. Develop validation possibilities.

In developing a stochastic model, we need internal as well as external validation criteria. Internal criteria include validation checks on elements within the data set. For example, we might test how well the derived N-step transition probabilities match the empirical ones. (See Shachtman et al., in press, for an example.) External validation is accomplished in terms of how well the model estimates known quantities such as well-established prevalence rates. This topic is further discussed in section V.E.5.

Many papers do not follow all of the above stages. One paper, however, does provide a quick review of stochastic modeling with an MC as a concrete example. In their article, Rodda et al. (1971) attempted to model the differential anxiety and depression patterns among 31 male patients with coronary heart disease and 46 healthy male controls. For illustrative purposes here, we consider the anxiety transition matrix for young subjects (i.e., under 50 years of age). To measure anxiety, the authors used a 10-question subset of the Bendig Manifest Anxiety subscale of the Minnesota Multiphasic Personality Inventory (MMPI). See Dahlstrom and Welsh (1960). Subjects answered true or false to 10 questions, such as "I get nervous if I sit for very long" and "I am usually worrying about something." They received a composite score from 0 to 10, and this scale was categorized to form three states: low anxiety (0-3), medium anxiety (4-7), high anxiety (8-10). The subjects were measured an average of seven times each over a period of 15 months. From these path data on each individual, Rodda et al. estimated separate transition probability matrices for young controls and young patients (figure 4).

FIGURE 4

ANXIETY LEVEL AT TIME N + 1

		YOUNG CONTROLS				YOUNG PATIENTS		
		Low	Medium	High		Low	Medium	High
ANXIETY LEVEL AT TIME N	Low	0.946	0.053	0.000	Low	0.812	0.187	0.000
	Medium	0.217	0.739	0.043	Medium	0.125	0.562	0.312
	High	0.000	0.200	0.800	High	0.000	0.150	0.849

Transition probability matrices for anxiety Markov chain

The first observation, that the controls tended to remain at lower anxiety levels than patients, could probably be determined from fixed-point observations and classical experimental designs. One can also see that controls have a much higher probability of remaining at a medium level of anxiety or moving to a lower level. Coronary patients, however, seem to have a higher probability of bouncing between high and low anxiety levels. This is a transitory phenomenon and is recognizable only through sequences of observations.

Among the advantages of these stochastic models over linear models such as ANOCOVA is the ability of the MC to produce time-dependent results and other parameterizations (functions of the transition probabilities). In particular, assuming the stationarity of the transition probabilities over time, we can derive expected results that are comparable to those obtained from a classical design. If at time 0 we have 10 people in each of the three categories (pre-score measurements), then we can derive the expected number in each category after a reasonable amount of time, say, five time intervals. The analytic results mentioned in step 5 above permit the computation of a five-step (in general, N-step) transition matrix directly derivable by taking the fifth (Nth) power of the one-step transition matrices given above (figure 5).

FIGURE 5

ANXIETY LEVEL AT TIME N + 5

		YOUNG CONTROLS				YOUNG PATIENTS		
		Low	Medium	High		Low	Medium	High
ANXIETY LEVEL AT TIME N	Low	0.837	0.145	0.013*	Low	0.451	0.287	0.257
	Medium	0.593	0.321	0.081	Medium	0.192	0.274	0.529
	High	0.252	0.377	0.369	High	0.083	0.254	0.658

*Rows do not sum to 1.0 due to roundoff error.

Five-step transition probability matrices for anxiety Markov chain

The matrices in figure 5 give the probability of being in state J at time 5 conditioned on starting in state I at time 0. For example, the expected number of patients in the medium state at time 5, conditional on the low starting state, is simply the number that started in L at time 0 multiplied by the probability of being in state M at time 5, that is, expected number = (10)p(L,M) = (10) (0.287) = 2.87 for coronary patients.

In table 2 we calculate these expected numbers for all combinations of starting states and states at time 5. The data in table 2 are comparable to post-score measurements from the analysis of covariance, if the measurements at time 0 represent pre-score values. From these data, a comparative set of interpretations can be derived for both the stochastic and classical analyses. An area for further research could involve determining whether stochastic

Table 2. Expected number in state at time 5, according to starting state

State at Time 0	State at Time 5	Expected Number in State at Time 5	
		Young Control	Young Patients
Low(10)	Low	8.37	4.51
	Medium	1.45	2.87
	High	0.13	2.57
Medium(10)	Low	5.93	1.92
	Medium	3.21	2.74
	High	0.81	5.29
High(10)	Low	2.52	0.83
	Medium	3.77	2.54
	High	3.69	6.58

modeling based on several distinct transition matrices is superior to classical analysis.

This type of analysis suggests the applicability of Markov models when measuring transitory phenomena, although it does not begin to plumb the analytic alternatives for evaluations after estimation of the transition matrix.

IV. STOCHASTIC MODELING PERSPECTIVES IN EVALUATION

In this section, we present two mental health program evaluation (MHPE) problems that stochastic modeling attempts to resolve, two types of MHPE measures, and a brief introduction to four MHPE papers using stochastic models. Detailed discussion of the papers appears in section V.

Stochastic models are especially applicable to program evaluation in mental health because of the large amount of variability in the psychodynamic processes of individuals. These models solve many of the problems inherent in the use of experimental and quasi-experimental designs. They utilize sequences of observations (rather than fixed-point observations) to reflect patients' psychological transitions. Chassan (1967) comments on how statistical models should capture the psychological processes of individuals:

> Not only is the patient to be described in terms of a multidimensional or multivariate probability distribution, but the study of change in the patient's state, or the evaluation of a patient's progress, or lack of progress, in the course of time in relation to any program of therapy, is then to be performed in theory by comparisons of individual variability. Such variability is the basis

> of defining the patient's state in terms of statistical distributions, or probabilities, estimated from sequences of observations of a given patient, and consequently provides the framework for the application of statistical inference and experimental design to the data of the individual patient.

We expand on Chassan's comment by emphasizing our aforementioned objective. We wish to make inferences about patterns of change, not just levels of change. We should achieve this by analyzing models for groups of "similar" patients.

In addition to variability, patient interaction may violate the necessary assumption that observations are independent in classically designed experiments; the interaction can cause such problems as the matched-pairs comparison mentioned in section II. These problems are especially troublesome in hospital ward settings where patients have close and continuous contact. In a stochastic view of modeling, patient interactions are part of the psychopathological process and should be included rather than excluded from the study. A transition probability matrix should be framed around the natural mental health unit, commonly a ward, producing a complete statistical picture reflecting patterns of patient interaction. There are still analytic problems in this area because estimation of transition probabilities assumes independence of observations; however, this type of complete ward analysis could start to provide the parameters of patient interaction (i.e., patient diagnosis mix, patient severity mix, number of patients in the ward, etc.).

There are two types of dependent variables commonly used in evaluation studies in mental health. We characterize them as program performance measures and patient functioning measures. Program performance measures focus on patients' utilization patterns in the mental health system. The patterns may reflect institutional movements. For example, Reuter and Young's (1980) study uses such states as walk-in unit, evaluation unit, general hospital clinical division, individual psychotherapy, couples-family therapy, and inpatient or outpatient community mental health centers. The patterns may also reflect intrainstitutional movements; for example, Eyman et al. (1967) use such states as in-hospital-and-enrolled in school program and in-hospital-but-not-enrolled in school program. Program performance measures reflecting inter- or intra-institutional movements may also be referred to as patient location measures, because they emphasize facility or type of service. Note that there are additional program performance measures, including service intensity (number of hours, visits) and labor intensity (transportation services).

On the other hand, patient functioning measures focus on the direct modeling of patient condition and behavior over time--the psychodynamics of the illness. Since mental illnesses vary so widely in their manifestations (i.e., the range includes schizophrenia and other psychoses, as well as anxiety, depression, paranoia, retardation, organic brain disease, and alcoholism), a wide range of patient functioning measures are applicable. Many standard measures are available (e.g., the MMPI), although patient-specific measures have recently become popular. The problem with the latter type of measure is that patient aggregation is difficult to achieve; yet the development of homogeneous groups is necessary for any overall evaluation of patient functioning.

The choice of the dependent variable differentiates among the evaluation studies using stochastic models. Trinkl (1974) and Meredith (1974) use patient functioning measures in an MC model to evaluate the effectiveness of different mental health programs. Trinkl uses a combined scale that rates independence in the living environment and in the working environment to develop a value-weighted MC. To obtain benefit-cost ratios, he compares the subjective benefit of the transitions made in each of five programs to the costs. Meredith uses an unweighted average of scores on eight self-help tests (ambulation, arm-hand use, toileting, expressive communication, receptive communication, feeding, bathing, and dressing), which are conducted annually, and obtains matrices for five different programs for the mentally retarded.

Eyman et al. (1967) and an earlier article by Meredith (1973) use patient location as the dependent variable to develop their models. Eyman et al. compare a matched set of mentally retarded children. One group attended a day school program as part of their hospitalization, and the other group attended industrial therapy classes. The analysis followed the two groups for 4 years after initial hospitalization with respect to their location status (in-hospital-and-dropped from school or industrial therapy class; in-hospital-and-attending class; released from hospital on indefinite leave). From this data Eyman et al. develop separate transition matrices for the day school and industrial therapy groups. Meredith uses an MC model to show that a geriatric resocialization program (GRP) is more cost-effective than a geriatric ward for placing patients outside the hospital. States for this model include the GRP, the ward, placement outside the hospital, and death.

V. IMPLEMENTATION OF STOCHASTIC MODELS IN EVALUATION

In this section we lay the groundwork necessary for identifying and describing problem areas in the use of stochastic models for mental health program evaluation. Subsequent research efforts should have the solution of these problems as a high priority objective. We employ the basic framework of section III and use the aforementioned papers, other health services research, and our research to illustrate the perspective, problems, and results.

The process of constructing a mathematical model as part of an OR study, whether for program evaluation or other use, involves a lengthy series of stages and feedback, testing, implementation, and evaluation before the modeling efforts are complete. It is not within the scope of this paper to elaborate on each of these subprocesses and interpretations of results. We have selected several stages from a version of a management science and operations research problem-solving process by Shachtman (1973). We comment only on those items that we believe have immediate implications as problem areas for MHPE modeling. They are as follows:

A. Initial consensus on objectives;

B. Variable definition and reporting requirements;

C. Design statistical planning;

D. Data collection; and

E. Researchable problems in analysis and model building.

A. Initial Consensus on Objectives

This first point derives from one author's experience with an organization whose mission is to monitor and evaluate mental health program services in a large urban area. Yet the finding underlines a general evaluation criterion independent of either MHPE or OR modeling. We observed the effect of competing, or at least uncoordinated, program objectives. In particular, there was a disparity between the target population of some of the programs and the client categories actually being served. Initial funding for the mental health services came from the State level and was directed toward structured objectives involving a spectrum of services.

Somewhat different objectives emerged, however, from the operational experiences of city officials and from a third group, community organizations responsible for direct contact with patients and clients. The differences became clear when we reviewed State eligibility requirements, which were based primarily on the frequency and time proximity of lengths of stay in State institutions. City and community agencies soon discovered that locating, contacting, and convincing "eligibles" to participate in these programs was not an easy task. Yet, the agencies were able to find other classes of individuals who needed the services they were equipped to offer. This was especially true for outreach (outpatient) programs. In another type of institutionalized program, administrators soon discovered tricks for satisfying the letter, if not the spirit, of the eligibility requirements for admission.

In short, the analyst-evaluator is faced with a complex situation. Should models be constructed whose outputs satisfy all the sets of objectives so that these outputs can be used to compare the competing objectives? Is the analyst-evaluator required to become the catalytic agent influencing officials from two or three different agencies to derive common program objectives? If those responsible for monitoring and evaluating program data do not take these objectives into consideration, their results will be deemed inadequate or nontargeted, even if they meet the criteria for one of the agencies.

Thus the MHPE process, aided by the OR analyst, must assist in deciding on program objectives and in coordinating these objectives among several groups.

B. Variable Definition and Reporting Requirements

Model construction should not begin until program directors reach consensus on objectives, on an evaluation approach, and on the variables keyed to objectives and evaluative measures. If program managers pilot a monitoring and evaluation project over a time span of 6 months or a year, there may be time to redefine these variables, but data collection processes are sufficiently difficult to require much thought when mounting the program. The OR analyst should be an integral part of the process of setting objectives and defining variables because he or she may have suggestions leading to better efficiency in the design of a data collection system--the necessary predecessor to effective analysis and model building.

Program evaluators and OR analysts also must choose among several types of evaluation designs and specify reporting requirements necessary to the design of the monitoring system. Program performance measures generally consider the amount of time spent on different types of program visits (case management, clinic visits, on-site rehabilitation), social center visits, outreach efforts, sheltered workshops, day treatment, development of coping skills, competency evaluations, and other services (homemaker, housekeeping, transportation). Program performance measures usually summarize the number of patients served, time spent, number of cases handled in different ways, and so forth.

Patient functioning measures, on the other hand, reflect outcomes of treatment. For some patient types, these measures reflect diagnoses, individual abilities to perform simple physical tasks, behavior problems, and environmental factors as well as occupational abilities. Physical health is an important factor. Note that these are only examples and may vary widely depending on patient and condition.

These variable definitions and reporting requirements lead to the state space definitions for stochastic models. Examples of resulting definitions are given in section V.E.

Finally, we would like to mention a special issue in psychological measurement that appears to lend itself readily to the stochastic modeling approach. We refer to it as the short-term/long-term change pattern. There are apparently two basic types of psychological instruments that can be utilized as patient functioning measures. Personality assessment scales (e.g., the MMPI) measure the average psychological level of a person over a certain time interval, which is usually not made explicit. The averaging is achieved subjectively through the use of questions containing phrases such as "do you usually . . ." or "When I encounter a certain situation, I . . ." The second type might be called mood monitors (e.g., Mehrabian-Russell Semantic Differential). These measure the present psychological frame of mind of the person and, thus, are less subject to selective recall than personality assessment scales. Theoretically, the patterns of moods over a certain time interval determine individual personality traits. For example, quick swings of depressive and manic moods determine the manic-depressive personality disorder.

Because of the small number of observations in classical designs, the subjective averaging is necessary; that is, the analyst does not want to record a measurement for a subject who is in a particularly uncharacteristic mood. This is especially true if the analyst has access to only one or two observations. If we are truly going to measure the changing patterns of change, however, the subjective averaging process will tend to lose information. Stochastic models, as a result of the number of observations on similar individuals, can measure patient functioning at its most basic level--the mood. We suspect that most of the stochastic models using patient functioning as their dependent variable still use personality assessment scales. Short-term measurements require frequent observations. Nevertheless, the payoff in tracking specific psychodynamic movements may be worth the effort and might not be expensive if performed as an adjunct to services delivered on a regular basis. Mood monitors, therefore, represent another area of potential research.

C. Design/Statistical Planning

1. Pilots and Sample Size

Once an evaluation criterion (e.g., program performance, patient functioning, or their combination) and related variables (measures of effectiveness such as those mentioned above) have been selected, statistical planning should ensue. Planning should include designing protocols for data collection and sample size estimation. Theoretically, these processes might occur concurrently with the piloting of program services delivery. Frequently, however, startup to a full level of services is rapid, and program managers make quick decisions on data collection, often with emphasis on the reporting requirements of the budget office. In these cases, programs may not be collecting the data most valuable for future evaluation.

The first task in statistical planning is the definition of the appropriate populations for data collection and, where needed, estimation of sample size. A program often summarizes population statistics, such as the number of patients served, totals of types of services, etc. These may encompass large groups of individuals with distinct subsets of mental deficiencies. In the latter case, if program management is interested in estimates of certain prevalence or incidence measures (e.g., the proportion of clients exhibiting certain levels of anxiety or depression and changes in these patterns), statistics must be computed from samples, provoking a need for estimates of sample size. With sample data in hand, the analyst may estimate the rates of prevalence and incidence for a particular deficiency in a broad target population.

2. Dependent Variable Induced Design Considerations

To illustrate certain concerns with design, we use stochastic modeling examples, although the design considerations are of general importance.

Clearly the choice of design depends on the choice of dependent variable under investigation, especially as it relates to a type of evaluation. The studies that use patient condition as a dependent variable (Trinkl 1974; Meredith 1974) develop transition matrices representing the course of a patient's stay in a particular program. These transition matrices for distinct programs are then compared. One assumption of Markov modeling is the time homogeneity (stationarity) of the transition probabilities--an assumption that the transition probabilities do not change over time. The purpose of a successful program, however, is to change the transition probabilities over time. For example, many "normal" individuals have brief periods of depression. A transition matrix may reflect this by representing a simple pattern of flow among levels of depression, with corresponding transition probabilities.

For a group with a higher propensity for longer, or "deeper," periods of depression, the effect of a successful program may be to modify the transition probabilities to result in a pattern with shorter, or "shallower," depression occurrences typical in "normal" populations. The MC at the end of section III, although it deals with anxiety, provides an example. In that case, the coronary patients exhibited a propensity for "deeper" periods (patterns) of anxiety.

The key consideration here is that programmatic efforts, especially direct services, contain interventions (one-on-one settings, group conferences, prescription of drugs) that affect transition probabilities. Thus, one is not nesecessarily able to obtain a static picture of patient outcomes to compare alternative means of delivering services.

An alternative design establishes a baseline transition matrix that describes and characterizes patient functioning before, or in the early stages of, the program. An OR analyst develops a program effect transition matrix using data from the later parts of the program or upon completion of the program. The latter design is especially applicable when using a patient functioning variable that tends to have a cyclic, or seesaw, property over time; one example is depression. We measure the program effect only in terms of the changing patterns of the cyclic process. Sometimes expert subjective estimates make up the corresponding transition probabilities when empirical data are not available. See Trinkl (1974) for an example.

For the coronary patient example, we may have to modify some of the transition probabilities and look at patterns of change in long-term stable behavior or other measures by means of powers of the modified matrix as a way to test the effect of an intervention intended to reduce patients' anxiety. Suppose we subjectively assume an increase in the probability of staying in the low anxiety state, p(1,1), for the coronary patients, for example, assume that p(1,1) is 0.9 rather than 0.812 (see figure 4). Then we may compare the probability of being in that state after five time periods, the p(1,1) element from the fifth power of the modified transition matrix, to the corresponding element from the fifth power of the original transition matrix, to examine the effect of the subjective assumption. It is with these types of dependent variables, for which we wish to measure the changing patterns of a transitory phenomenon, that the clear superiority of stochastic rather than single fixed-point pre- and post-program measurements is apparent.

Employing program performance measures as dependent variables in a program evaluation alters the focus of a study. These variables may effectively measure costs and utilization, but they remain at best proxy variables for patient benefit. For example, although Meredith (1973) computes only the long-term relative costs of the geriatric ward versus the GRP, he assumes implicitly that more rapid deinstitutionalization of the GRP patient is beneficial; that is, if someone is discharged from the hospital, his or her health must have improved. This is a dangerous assumption, especially because the modern trend toward early deinstitutionalization makes premature release possible. An OR analyst must base conclusions concerning patient benefit on patient functioning variables unless the validity of patient location as a proxy variable is well established. This is not to say that evaluation studies should categorically avoid patient location. In many instances, especially in the care of the severely ill, a program's purpose involves the maintenance of patient status rather than improvement. The gains from such maintenance programs can come through lower costs and more efficient utilization of services.

Early evaluations of psycopharmacological agents used patient condition indicators as dependent measures. With the increase in deinstitutionalization, the emergence of community mental health centers, and concern with other aspects of community support programs, there is a growing need for global evaluation of interlocking programs. For these applications, patient location measures have become easier to obtain and are often considered to be more reliable.

We may question whether global evaluation is the most appropriate choice for evaluating the impact of community support and other mental health programs, especially if it implies the use of patient location measures only. With the increased emphasis on consumer presence on community mental health center boards, informed consent for patients or clients, and public clamor for accountability, there may be a requirement for patient condition evaluation for specific subcohorts in addition to other measures.

D. Data Collection

In this section, we briefly touch on a very involved issue--the management of large data bases. This includes managing protocols for coding, collecting, converting to machine-readable form, automatic and manual editing, further testing and creation, and maintaining backup systems. See Jampol et al. (1979) for further details on a large study. Many mental health programs are large enough to justify use of computers, but the problems inherent in this stage of preparation for analysis are underemphasized.

The OR analyst should be well aware of the intricacies of data bit definition, its accessibility, its reliability with respect to content coding in the collection process, the quality of the edit system, and any quality control systems meant to check on data processing efforts. Our experience with large data bases, even when they are derived from a carefully controlled institution-based study (345 hospitals with detailed patient data, for example), has taught us that lack of care in considering these issues can severely affect the quality of model building for evaluation efforts.

An underlying problem with many evaluation analyses is that data collection proceeds with other intentions (usually for patient records or monitoring purposes), and the evaluation analysis is designed to "fit" the data. This problem could be acute in the collection of path data for stochastic processes. Mental health service systems usually collect extensive data upon a patient's entry and departure, in addition to data on the various services used during the stay. Outpatient clinics probably keep fewer encounter records because there is no continuum of patient contact. An analyst may often derive path-coded patient location or patient utilization data from these records, but systematic patient condition data collected at periodic intervals may be a rare commodity.

Record linkages between various health service systems are even rarer. There are, however, several progressive new recordkeeping systems under development. Honigfeld and Klein (1973) developed a data system that produces "fever charts" showing the patients' week-to-week progress with respect to relevant patient condition variables. Nonetheless, clinicans were not enthusiastic about utilizing these standard forms. We suggest that a chart review technique could be developed that would be similar to medical chart review techniques designed to extract information from hospital records for epidemiologic studies. This technique, along with additional protocols for chart entries, would insure sufficient data bits for such "fever charts." We have some experience with a targeted chart review technique that yields inference on infections acquired in the hospital. Validation analyses suggest that it is successful (Haley et al. 1980; Whaley et al. 1980). In another example, Bloom (1972) has developed a patient-tracking rather than a service-component-oriented data base.

Missing linkages and event information also pose research problems for the estimation process in stochastic processes. See section V.E.2.

E. Researchable Problems in Analysis and Model Building

We discuss some of the stages of stochastic model building, with concurrent criteria, from the task list given in section III. Our objective is to point out several areas that merit caution in construction and application of the models, while noting that they also provoke researchable problems. Some initial results for these problems are available.

1. Homogeneous Subgroups

a. The problem. Greenhouse and Kramer (1959) identified the need to obtain a homogeneous group of patients for valid evaluation studies in mental health. Today, especially with the effects of deinstitutionalization, the problem of obtaining a fairly homogeneous group with similar mental deficiencies at one time is even more acute. One assumption for Markov chain analyses is that the transition matrix for a typically selected individual in the study (theoretically obtained by following that individual over an infinite amount of time) should approximate the transition matrix obtained from an aggregation of people measured for finite amounts of time. This is known as person-to-person homogeneity. The probabilities of a patient moving from state to state, for example, each of which represents a functional level, clearly may vary with patient age, previous history of institutionalization, characteristics of the outside support system, and other factors not necessarily reflected in the state structure of the model being used. We refer to this as the heterogeneity problem.

If we cannot solve the heterogeneity problem in a reasonable manner, then our ability to generalize results from these sorts of models is compromised severely. The key to this problem is that when one develops separate transition matrices for comparing two programs, statistically significant differences between the two transition matrices may be more a function of an imbalance of relevant or covarying characteristics than of the actual difference between the two programs. Therefore, the analyst must at least develop suitable measures of what program managers are willing to consider as homogeneous populations.

b. The literature. The articles reviewed in section IV, which apply stochastic models to program evaluation, attempt to deal with the heterogeneity problem. Meredith (1973) is cognizant that each patient's probabilities of movement through the geriatric resocialization program may depend upon his or her individual diagnosis, the GRP's overriding consideration for selection, and the patient's amenability to resocialization. He points out that the last characteristic automatically results in the selection of a group of nonsenile patients who can generally be described as "burned out" (a medical term referring to the deterioration of the original illness over time and the consequent substitution of institutionalization symptoms). For this reason, the patients all show a surprising similarity. Thus, he treats them as one homogeneous class with identical transition probabilities "regardless of whether an individual patient was originally, for example, a schizophrenic female or an alcoholic male." He makes no attempt, however, to prove this point by estimating the transition matrices for groups of patients with different diagnoses.

Eyman et al. (1967) compare school and nonschool groups. They admit that there is no way to determine which changes in the school group are due to the program itself, over and above the factors involved in selecting patients for the program. They match patients by age and IQ to reduce the problem of differences between initial groups. Because patients within a group or ward interact with each other, thus affecting each other's mental state, a different patient mix can cause invalid results even when homogeneous subgroups from each of the programs are compared--recall our example in section II.

Meredith attempts to obtain homogeneous subjects by selecting individuals who are profoundly and severely retarded (IQ strictly less than 35), not physically handicapped, and under the age of 15. Because the hospital's treatment programs are not meant to apply to the full ability range of children, there is a severe problem of differences between initial groups.

Trinkl (1974) notes the inability to obtain enough data for estimating transition matrices if these matrices were estimated separately for each homogeneous subgroup. He states:

> It could be argued that a finer classification of states reflecting health status, degree of handicapping condition, age, and other socioeconomic conditions, is important to obtain well-defined transition probabilities, and, consequently, an immensely larger number of states is appropriate. If this approach were taken, conventional cost-effectiveness could be applied to evaluate specific provisioning of services for homogeneously defined groups of mentally retarded adults, but it would have been exceedingly difficult to evaluate alternative system approaches.

Trinkl obtains separate subjective estimates of the transition probabilities from several expert groups for each of the alternative programs. This technique could be extended to deal with heterogeneous subcohorts.

c. Stable baseline transition probabilities. The problems presented seem to point to the necessity of establishing stable baseline transition matrices against which we can measure change. In establishing a stable baseline, we must know what group of relevant characteristics or symptoms defines a particular mental illness. This brings up the definitional problem in mental health so vividly illustrated by the study in which videotaped sessions with patients shown to English and American psychiatrists yielded widely differing diagnoses (Kendell et al. 1971).

We suggest that different transition matrices could be formed for different sets of potentially relevant characteristics until transition matrices were found that were stable over different studies and situations. These transition matrices would abstract defining characteristics of a particular mental illness and could provide stable baselines for later evaluation studies.

d. Two strategies for developing stable baseline transition matrices. There are two basic design strategies for developing stable transition matrices. We may conduct an "intensive design" by following a few subjects (or even one) over a long period. The matrices may evolve from real or subjectively estimated data. Researchers who feel that mental processes are so variable as to preclude large-scale studies or global evaluation advocate intensive designs. One advantage of such studies is the possibility of tailoring dependent psychological measures to the small group of people in the study. We can also make the sample homogeneous with respect to many relevant characteristics because very few subjects are under study.

One might raise the objection that although any results obtained are certainly valid, they can be extrapolated only to the subpopulation, which consists of people with identical characteristics, that is, to the very small populations of people in the study. Strictly speaking, this is true, but Chassen (1960) believes that decisions on how to treat a given patient, based on previous experience with other patients, do not necessarily demand that our given patient's relevant variables be identical to those of preceding patients. We base decisions on similarities rather than complete identities. If patient characteristics are completely specified, the results of one study may lead logically to the formulation of its successor. Thus the patient parameters under study can gradually be broadened to include a wide range of patients.

The "extensive design" appears to be more applicable to evaluation studies. We conduct such studies by trying to choose relevant variables to form homogeneous subgroups from a large sample of the population.

The first method of achieving this goal is to form separate transition matrices for each level of possibly relevant, discrete covariates, combining matrices that are not shown to be statistically different. Rodda et al. (1971) use the Bendig Manifest Anxiety subscale and Welsh Pure Depression subscale of the MMPI to develop stable transition matrices for 31 male patients with coronary heart disease and 46 healthy male controls. They match each patient with a healthy control on age, sex, race, education, occupation, and height and weight. Previous research has shown age to be a factor, so separate matrices were developed for young (under age 50) controls, young patients, old controls, and old patients on each of the two subscales. See the example at the end of section III.

There are several problems with this approach. One is the obvious aforementioned problem with the quantity of data required. Another is what might be termed the "identifiability" of the groups; see Thomas (1968), for example. In this problem, one is faced with determining how to state conditions or diseases. Can we use a single state, or are multiple states necessary? Do we need multiple chains? Several approaches compromise between trying to reflect all the variables under consideration in separate models (chains) for separate groups and trying to combine all groups into a single model. See Shachtman et al. (in press), who construct separate subchains for aborters of a first pregnancy but combine states for reproductive behavior after the first delivery.

Other techniques for overcoming the heterogeneity problem are directed at adjusting for covariates. One is Spilerman's (1972) technique, which is based on multiple regression. Reuter and Young (1980) discuss this and point out that Spilerman's work is simply a generalization of the separate cohort approach to the extreme case where subcohorts contain individuals. It is clear that in this case only a single transition is predictable, because the prediction of subsequent transitions requires knowledge of the new distribution of characteristics in each state at each time period. We would have to have these predictions for each of the individuals involved, or, in a slightly more general case, for each group. The question is, How might we convert this approach to represent appropriate heterogeneity without severe computational costs and data requirements? Reuter and Young go on to develop an alternative approach to the population heterogeneity problem.

A third method for achieving homogeneously defined transition probabilities and covariate adjusted transition probabilities is still in its early stages of theoretical development (Fertig et al. 1979). This technique allows for continuous covariates and could be used more easily in a modeling sense than the standard technique of forming separate transition matrices for every level of discrete covariates.

2. Partial Path Observations and Aggregate Data

All studies must deal with the problem of missing observations. For example, there may be variables in a hospital study concerned with a rare disease and unusual therapy so that there are few observations for those particular variables. This type of missing information is a function of the scarcity of occurrence of condition/therapy pairs. Another problem of missing information surfaces when there may be many potential observations (e.g., the numbers of a relatively common surgical procedure) but, for some reason, a large proportion of hospitals have no observations of the procedure. Are these observations truly missing or does a particular study miss them because of design inadequacies?

The nature of this problem takes on a different form when we consider stochastic models and observations of mental health patients, especially to determine measures of patient functioning. To illustrate this problem, consider the following programmatic concerns and an artificial example. With the current trend toward deinstitutionalization, the recent increase of community support programs, and the linking of other social support services to clinic- or institution-based services, many more variables emerge as we define events in a mental health patient path. Some researchers refer to these sequences of events as micropaths (see Lee et al. 1970). A path would, theoretically, contain the psychological status and program encounters of every patient at every time period being measured. In some community support programs, we may be able to track a patient from an institution to certain clinic visits, but, for many patients, we may "miss" information on social support, nature of activities, occupational contacts and influences, and other institutional supports not directly connected with facility-based mental health care services. A worker in a community mental health center may derive some of this information from a careful interview and, possibly, link other institutional information, but may find very little information on some of the variables for some patients. We refer to this type of missing data as the partial path observation problem. This problem appears to be more significant for mental health program evaluation than, in our experience, it is for hospital-based studies (Kastner et al. 1979) and clinic/home based studies (Shachtman and Hogue 1976; Shachtman et al., in press).

Therefore, procedures for estimating patient status and progress, as well as the effects of intervention, are absolutely necessary. These procedures are all the more important when we wish to measure time dependencies and pattern changes. Clearly, no model can help supply information when there are no data, or expert opinion, on which to build the model. Frequently, however, stochastic models have the advantage, as with parametric models for statistical inference, that with few data of decent quality one may estimate some parameters and test different patient flows and outcomes with respect to different interventions. This advantage is clearly demonstrated by Trinkl (1974) and other authors who are able to employ standard techniques of sensitivity analysis on transition probabilities even when the original transition probabilities did not come from a data base. (Sensitivity analysis on parameters means that the analyst varies an input parameter, such as a relapse rate, holds all other input parameters constant, and measures the effect on an output measure, such as the eventual prevalence of institutionalized patients.)

We illustrate our concept of partial path observations, and the need for estimation techniques, with an artificial example. Consider a set of states that include patient status as indicated by events occurring to patients who are institution-based or clinic-based, and as derived from intensive interviews for events that cannot be observed in either a hospital or a clinic. Suppose that we have numbered these states, which may include patient functioning measures, from S1 through SN. We illustrate the paths of M patients visiting some of these states over time (figure 6). The asterisk represents a missing event observation for patient 1 at time 2.

FIGURE 6

Time Periods

			1	2	3	4	5	6	. . .	10	11	12
Patients	1		S5	*	S5	S2	S2	S2	. . .	S3	S3	S3
	2	. . .										
	3	. . .										
	/:/											
	17		S5	S7	S5	S4	S4	S2	. . .	S3	S3	S3
	/:/											
	M											

*Asterisk represents a missing event observation.

State occupancies by patients over time

The objective is not to impute a state occupancy for patient 1, e.g., by guessing that it is S5 because patient 1 is in S5 at times 1 and 3. However, we may be able to estimate additional transitions for a cohort of patients including patient 1 to "replace" his or her unknown transitions, (S5 -> *) and (* -> S5) during periods 1 through 3. For example, patients 1 and 17, along with other patients, may be statistically similar and the * occupancy may be replaced by S7.

Another type of incomplete observation may result from knowing only the proportion of a cohort that visits certain states at a given time. This is known as the aggregate data problem. Lee et al. (1970) summarize several schemes for estimating Markov parameters from aggregate time series data. Shulman and Shachtman (1978) suggest several schemes and an approach for aggregate data for semi-Markov processes.

Since mental health program evaluation analyses are even more likely to encounter the problems of partial path observation and aggregate data, the need for useful statistical procedures here is evident.

3. Developing State Definition Structure

Redefinition of the state structure often occurs to satisfy more closely other Markov model properties (e.g., time homogeneity and the Markov property). Sometimes one may also use redefinition to control for some of the heterogeneity problems. This technique was employed by Shachtman and Hogue (1976) to separate reproductive events for aborters and deliverers of first pregnancies as indicated above. We altered state definitions successively until statistical tests showed that the empirical results did not violate the assumptions. Similar definitions might be made for mental health patients after an extended period of working with their first levels of diagnosis and treatment in the system. A combined set of states might be used for "maintenance" patients. For another health example dealing with the redefinition problem, see the MC formulation in Thomas (1968) and the later semi-Markov version in Kao (1971).

A separate issue in defining states is the determination of which events for a mental health patient help to define a state. For example, if our objectives require patient functioning measures and we define states using levels of anxiety or depression, we may need interim measurements from notes made by a psychiatrist or a social worker. A definition, perhaps algorithmic, would have to be made to translate the assessments made by these professionals into states of anxiety or depression. If the number of patients flowing into a community mental health center or other program is large, there would have to be an unambiguous set of definitions so that a computerized algorithm could translate patient events into patient states.

4. Higher-Order Markov Dependence

Using a higher-order MC, or an expanded first-order MC, theoretically involves the Nth-order problem referred to in section III. From both the heavy data requirements and a computational viewpoint, however, this is usually an impractical solution. A compromise is to collapse some information into single states, for example, allowing certain states to represent a composite measure of the patient's psychological status, while not trying to represent all of its attributes. Such a consolidation of information occurs in Trinkl (1974). He derived four levels of living environment and five levels of work environment, which, after deletion of three inappropriate states, yielded seventeen combination states. This appeared to be successful for his particular application.

Sometimes allowing a second-order property to be satisfied may be acceptable, as in the reproductive events defined for the estimates of time to delivery in Shachtman et al. (in press). In such cases, one may be able to prove statistically that the first- and second-order properties are the same, justifying a first-order MC. In general, a certain amount of cleverness in designing state spaces will overcome these difficulties.

5. Validation

Validation is a difficult topic and well deserves a paper itself. Several approaches to validation are independent of the modeling processes used. For example, we may construct a model on a randomly selected subset of the data base and compare it to one we construct on a disjoint subset. With MC and semi-Markov models in particular, one may often compute transition matrices for various subsets and compare the matrices statistically. Another type of validation, although it must be carefully interpreted, is to compute functions of the transition matrices and compare these functions, not only with each other, but with certain empirical calculations of incidence of prevalence rates (see Schoenfelder et al. 1980, and Shachtman et al., in press). We found no examples of the use of validation techniques for mental health analyses, let alone for program evaluation, in the literature we reviewed. In fact, validation of models in health services research is rare. Often nonavailability of data is one of the problems. It may also be that the structure of the chain is acceptable to the decisionmakers and there are no data with which to compare model outputs, as occurred in Trinkl's work.

One should be very cautious about the type of validation procedure one uses. For example, suppose we estimate two transition matrices, A and B. We may wish to compare these matrices statistically to see if they are the same. Furthermore, we may be interested in certain functions of these matrices, f(A) and f(B), to calculate whether a particular interesting set of states (pattern of mental deficiency) is visited, perhaps states in which the patients are "doing better." Figure 7 displays the possibilities with our own assessment of the intuitiveness of the combinations. All combinations I, II, III, and IV can occur. An example of III for a non-mental-health problem is given in Shachtman et al. (in press), in which the two transition matrices, A for the aborters and B for the deliverers, are different. Thus their movement behavior is different. Yet the functions of the transition probabilities that calculate time to the next delivery of a pregnancy are the same: f(A) = f(B) statistically. Moreover, the latter two calculations were also the same as the actual frequencies of these times observed in the two data bases. In this particular case, we were able to validate the calculations of time to delivery while showing

FIGURE 7

Functions of Transition Matrices

		f(A) = f(b) statistically	f(A) ≠ f(B) statistically
Transition Matrices	A = B statistically	I Intuitively expected to occur	II Non-intuitive but can occur
	A ≠ B statistically	III Non-intuitive but can occur	IV Intuitively expected to occur

Equivalence combinations between transition matrices and their functions

that the basic movements were different. Hence, validation techniques can be very useful in interpreting the results of these movements but must be applied very carefully.

There are several instances in the MC evaluation papers in which the mathematics of stochastic processes is correctly applied but validation through external criteria is lacking. The most flagrant example of a case to which this criticism applies is Meredith (1974). He develops a transition matrix based on the data from two annual measurements (i.e., the transition matrix was based on one transition only from the 1970-71 data). From this transition matrix, a 1970-74 four-year transition matrix is computed by taking the fourth power of the transition matrix. Meredith states that this matrix "may be used not only for individual patients but also to ascertain the expected future distribution of the initial cohort." This is a case of extreme extrapolation beyond the end points of the data. Certainly the transition matrix might change over the course of 4 years, especially when the initial matrix is based on only one transition. These results should be validated on the basis of either prior substantive knowledge concerning the time homogeneity of the chain or 4-year path code data collected on at least one subset of the individuals in the study.

VI. RECOMMENDATIONS

A. Objective Setting

The OR analyst, as an evaluation team member, should participate with program managers and funding agency officials in the consolidation of potential objectives. The group should reach a consensus on those for which monitoring and evaluation will be performed.

B. Development of Data Systems with Monitoring/Evaluation in Mind (whether or not model-building is involved)

1. Data collection and management, although tedious, may require more time than that spent on modeling for mental health program evaluation. Routine needs for data management--including editing, processing, and redefinition--should not be overlooked.

2. Patient functioning variables should be recorded as standardized measures at periodic intervals.

3. Patient tracking/record linkage across health service systems is difficult to achieve but, even if available only on subcohorts, is well worth performing. That is, a few high-quality observations lead to useful models. This is a statistical power concept for Markov models that is not unlike the concept of power for parametric statistical inference.

4. Computerized data base systems should be established if they are not already in existence.

C. Evaluative Measures

1. An area with great potential for research and implementation is the linking of a sufficient battery of program performance and patient functioning measures. These measures must exceed budgetary reporting requirements and allow the type of evaluation we have emphasized here, namely, the ability to detect changing patterns of change. This type of research will necessarily involve interdisciplinary teams that include psychiatrists, psychologists, analysts, and program managers with experience in the accessibility of key variable information, for the construction of appropriate scales.

2. Given the advantages of stochastic modeling, more use should be made of patient functioning in addition to program performance measures.

3. We should study the possibility of using psychiatric records to obtain patient functioning levels on a more regular basis, perhaps by chart review techniques.

4. We should investigate the utility of mood monitors in addition to personality scales.

D. The Heterogeneity Problem

The problem of heterogeneity is a significant area for research, and several directions may be feasible.

1. We should investigate the use of stable transition matrices to help define and differentiate mental illnesses.

2. We should support basic statistical research in the area of covariate adjustment in stochastic processes.

E. Incomplete Observations

Another key area is the research needed to overcome the partial path observation and aggregate data problems.

F. Parameterizations

As a special point, we note that, although researchers have constructed stochastic models and performed simple analyses with the resulting transition matrices when these models are Markov chains or semi-Markov processes, they have not tapped the potential for further analyses; that is, one may construct many functions of the transition probabilities to meet specific objectives. We have no examples of this use of transition matrices in mental health evaluation research, but have been able to create such functions for several other examples (Kastner et al. 1979; Shachtman and Hogue 1976). In addition to what we can learn from performing sensitivity analyses on the transition matrices, the same sensitivity analysis may be performed on functions of the transition matrices to yield even more information about the pattern change behavior for mental health patients.

G. Subjective Estimates/Expert Opinion Input

Finally, we should not undervalue the potential to apply subjective parameter estimates (e.g., transition probabilities), especially when dealing with the heterogeneity problem and other problems where direct observation is impossible or too expensive. Trinkl (1974) was able to use this approach with some success, and other health services applications have been able to utilize these techniques.

In summary, the data requirements for Markov chain and semi-Markov model building need not be expensive. The assumptions of the models, plus the strengths indicated in points B.3, C, F, and G above, suggest that these approaches are cost-effective for mental health evaluation research.

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Chapter 3.

RESEARCH NEEDS FOR RESOURCE ALLOCATION IN THE MENTAL HEALTH SERVICE SYSTEM

Judith S. Liebman, Ph.D.

I. INTRODUCTION

The potential contributions of operations research to the improvement of the mental health service delivery system are extensive. Close to 15 percent of the U.S. population needs some form of mental health services, and, in addition, approximately 6 million people in the United States are mentally retarded. This is a sizable segment of our population, and the current trend toward third-party reimbursement is expected to contribute to increased use of mental health services. Hence, it is imperative that we develop methodologies to allocate our mental health system resources as efficiently as possible. Operations research has frequently been used to aid resource allocation decisionmaking in the general health care delivery system (Fries 1976; 1979). This research provides a foundation and a framework from which applications of operations research may be developed specifically for the mental health service system.

A crucial, initial step in applying operations research is to determine those resource allocation decisions that are important and the levels of the mental health care system at which these decisions are being made (or at which the recommendations for alternatives are being developed). It is also crucial to identify the decisionmakers, the various types of information and models that will be of greatest use to these decisionmakers, and the goals and objectives by which the outcomes associated with the resource allocation models will be evaluated.

The organization of this paper is as follows. First, there is a discussion of the hierarchical nature of the resource allocation decisions in the mental health service system. Next, the types of resource allocation decisions at each level are categorized. The third section of the paper summarizes briefly the types of resource allocation methodologies available in operations research. The fourth and major section provides specific suggesions for applying operations research to aid resource allocation decisionmaking in the mental health service system. In some instances, the application of operations research is straightforward. In other instances, allied research may be required to extend the capability of the operations research methodology or to extend our knowledge of cause-and-effect relationships in the mental health service system. The final section provides a summary list of recommendations for research. Because the annotated bibliography (Scott 1979) supplied to the conference participants discussed the research to date in developing resource allocation models for the mental health service system, this paper does not include a comprehensive summary of past research.

II. RESOURCE ALLOCATION IN THE MENTAL HEALTH CARE SYSTEM

As indicated in figure 8, the major levels in the mental health care system at which resource allocation decisions are made are Federal, State, regional, and local. Local decisionmakers include individual agencies, individual providers of mental health care, and individual patients.

At the upper levels (regional, State, and Federal), the decisions entail the allocation of funds, the creation of guidelines and regulations, and approval or disapproval of proposed programs. Agencies, programs, and facilities at the lower level use these funds and authorities to provide the actual resources used by individual providers in the process of treating patients.

At each level, it is important to determine (1) which decisions (or types of decisions) are allocating significant proportions of funds and resources, and (2) which decisions have the greatest potential for changing the mental health of the population.

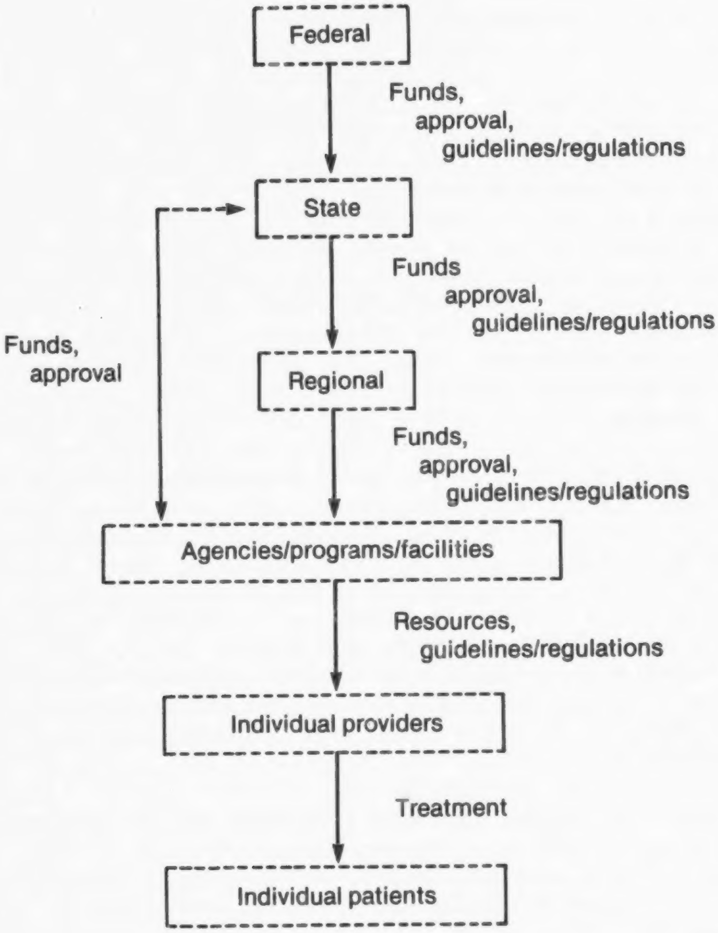
At each level of decisionmaking in this hierarchy, there is an allocation of limited resources, most often among competing alternatives. It is important to note the simultaneous influence of decisionmaking from upper levels (provision of funds, guidelines, and regulations) and the influence of requests for resources and approval from the lower levels. At each level, relevant decisionmaking that affects the mental health service system also is occurring elsewhere in the overall general health care delivery system. The modern tools of operations research can greatly aid decisionmaking within this complex framework.

III. RESOURCE ALLOCATION METHODOLOGIES

A major category of methodologies that lend themselves to resource allocation decisionmaking is mathematical programing. In mathematical programing, descriptive models of the system are constructed and then optimized. When solved, these models indicate which resource allocation alternatives are feasible and, of these, which alternatives best meet the system objective(s). Feasibility is controlled by representing the system interrelationships and requirements as functions of the decision variables and other system characteristics called state variables. Functions of these same decision and state variables also characterize the objective of the system. Depending on the functional forms used when building the system model, numerous mathematical techniques are available to obtain solutions and to explore the sensitivity of these solutions to changes in model form and parameters.

A particularly valuable subcategory of optimization models are those embodying networks. A network-based representation of the flow of resources provides an exceedingly useful picture of the resource allocation process. It enables all system decisionmakers to better understand the resource allocation process and to participate in the design of the model. Their active participation hastens model validation and implementation.

FIGURE 8


Federal
Funds, approval, guidelines/regulations
State
Funds approval, guidelines/regulations
Funds, approval
Regional
Funds, approval, guidelines/regulations
Agencies/programs/facilities
Resources, guidelines/regulations
Individual providers
Treatment
Individual patients

Hierarchy of resource allocation in the mental health service system

Many times, the stochastic (probabilistic) aspects of a system under analysis are essential components and must be modeled directly. Most commonly in these instances, computer-based simulations are developed in which the interactions and complexities of the system can be modeled directly. Such simulations may or may not be stochastic and may or may not involve the solution of simultaneous nonlinear equations. Occasionally the stochastic elements of the system satisfy the necessary conditions to be analyzed as Markov or semi-Markov processes or directly as queuing processes.

Markov and semi-Markov models are useful classes of models in which the system is represented as being in one of an infinite or finite number of states, and, during any time period, there is some probability that the system will undergo a transition from one state to another. System rewards or costs may be associated with particular states or transitions. Markov decision processes model the effect of making investments to change the transition probability or reward structure or both. Specific algorithms (methodologies) are available to determine which set of investments is most desirable for minimizing overall costs or maximizing overall rewards. Sometimes a subclass of Markov processes can be studied as a queuing (waiting line) system, a particularly useful type of model because waiting lines, like networks, are a popularly understood phenomenon.

When the number of alternatives to be explored is relatively small, decision tree analysis can be used effectively. The underlying network format of decision trees also provides an easily understood framework within which to assess the important details associated with each alternative being examined. Decision tree analysis is being used as a diagnostic tool in medicine today.

A major limitation of these methodologies is that it is necessary to be able to describe aspects of the mental health system relevant to the decisions at hand in terms of either deterministic functional relationships or probabilistic relationships. At the very least, it is necessary to hypothesize these relationships.

Each of these approaches has extensive requirements for data, and these data must either be available or be estimated. The use of hypothesized relationships and estimated data is neither uncommon nor unwise. During the early development of models, it is important to experiment with a variety of functional forms and levels of detail. The results of this early experimentation often provide useful guidelines as to which functional relationships and which data are the most important to consider in future developments and applications of these models.

Potential limitations of these methods are associated with the efforts needed to obtain solutions after the model(s) are formulated and the data collected. Almost all these approaches entail the use of the computer to obtain solutions, and some very simplistic-appearing models require enormous, and sometimes unavailable, amounts of computer resources.

A final important methodological characteristic is the ease with which a particular model lends itself to sensitivity analysis, which is the process of varying input system parameters (i.e., data and functional forms) and evaluating system response. Sensitivity analysis is crucial in developing resource allocation models for the mental health service system for several reasons:

1. These models will have to be predictive to be useful;
2. Hard data in mental health services frequently are lacking;
3. Mental illness rates vary widely among populations; and
4. Knowledge of underlying processes related to mental illness and means to prevent or affect mental illness is lacking.

IV. RESEARCH QUESTIONS

In this section, we examine first the need for developing evaluation criteria appropriate and responsive to alternative resource allocation policies. Next, we examine a variety of mental health service decisions amenable to the application of operations research, beginning at the Federal level and moving through the hierarchy to the level of patient treatment.

A. Evaluation of Alternative Resource Allocations

One measure of effectiveness of resource allocation is self-evident. If resources are assigned to a particular category and remain unused (e.g., unused beds in state mental hospitals), then that allocation of resources is currently ineffective. A related measure is that of productivity. If researchers were able to develop appropriate measures of productivity in various mental health care settings, and if information systems were able to track and report on this productivity, then managers would be able to explore and perhaps control unexpectedly large deviations in productivity levels.

To discuss the appropriateness of allocation of funds for mental health services unfortunately raises the difficult issues of defining mental health and the populations at risk of having poor mental health. Commonly used general measures of health are mortality (life expectancy or standardized mortality ratios), morbidity, and disability (defined as a temporary or long-term reduction of a person's activity as a result of an acute or chronic condition). Commonly accepted measures specific to mental illness do not exist, although efforts toward the development of such measures are currently under way. Moreover, even if we could define appropriate measures of mental health status, crediting changes in mental health status to particular programs (e.g., private sector settings, community agencies) is not usually possible. The changes in status occur over such long periods of time that it is generally impossible to isolate the major influences.

Evaluating even such noncontroversial items as overall cost is not simple. Methodologies are needed to enable us to evaluate the total lifetime costs of a disability, including the costs to the individual, the State, the Federal Government, the third-party payer (such as an insurance company), and the employer (because of reduced productivity).

There has been some success in developing cost-effective criteria for certain specific types of mental health services, such as drug abuse treatment (Goldschmidt 1976; Votey and Phillips 1976) and alcohol abuse treatment (Swint and Nelson 1977; Hertzman and Montague 1977). Perhaps a paradigm for employing evaluation criteria similar to the paradigm developed for forecasting needs for health care services can be developed. One such approach is presented by Harrington (1977). In Harrington's paradigm, the potential effectiveness of major forecasting techniques, ranging from the use of informal historical analogies to the use of formal decision theory, is evaluated by the analyst for each of several factors present in demand forecasting situations (incidence of disease, accessibility and availability, types of existing health facilities, etc.). The evaluation of the forecasting effectiveness includes consideration of both validity and precision.

The mental health service system has a variety of areas for potential investment. We need to distinguish among the use of funds for (1) prevention (e.g., early alcohol abuse detection and counseling), (2) restorative services, and (3) maintenance. The age cohorts of the population with needs for these programs must be studied, and the equivalent of the "quality years-of-lives saved" measures being developed in the area of technology assessment should be developed. In this case, though, to develop such a measure will be even more difficult, because in most instances we are not talking about deaths versus lives but about lives spent at lesser or fuller functional capacity.

Furthermore, if the initial investment is not successful, additional investments may be called for. There is need for research to learn whether the recidivism analysis applied to correctional release programs (Stollmach and Harris 1974) can be a useful tool for evaluating alternative mental health treatment programs, for example, alcohol- and drug-abuse treatment programs.

The entire concept of benefits from treatment must be extended. Hertzman and Montague (1977) include income preservation, reduction of morbidity and mortality, restoration and enlargement of capabilities, and relief of "pain" among other benefits. One of the best analyses of the use of cost-benefit analysis and cost-effectiveness analysis in alcohol-abuse treatment programs has been done by Swint and Nelson (1977), whose work integrates the analysis into a health planning framework.

Another major question needs to be answered. Before authorizing large-scale Federal reimbursement for mental health care, a process clearly must be developed for identifying on the basis of proven efficacy those mental health treatments that should be authorized for reimbursement. Resource allocation problems underlie even this identification process, as in the controversy underlying the proposed National Institute of Mental Health (NIMH) study of the efficacy of psychotherapy (Marshall 1980).

The entire spectrum of multiobjective resource allocation emerges as an area needing research. Although research in multiobjective mathematical programing techniques is well under way and there have been extensive applications in such areas as water resources planning, application of the techniques in the health sector appears to have lagged. For example, staff allocation models for mental health facilities (Lyons and Young 1976) could be expanded to incorporate multiple objectives, including the original objective of appropriateness of care. In addition to the primary objective of improving the population's mental health status, other objectives are related to such concepts as accessibility (architectural, financial, and informational), cost, quality, and acceptability.

The use of goal programing in particular has great potential for the health system framework. Goal programing is a variant of mathematical programing, in which the objective is to minimize the sum of weighted deviations from prespecified goals.

Another potential approach to multiple objectives is stochastic process analysis. Meredith (1976) used Markov decision processes to optimize the discounted expected net benefit of alternative placements for mentally retarded patients. Research is needed to explore multiple objective decision processes. A possible mechanism for incorporating multiple objectives is to define multiple cost matrices, each of which represents deviations from ideal levels. Then, as in goal programing, one can seek an alternative that minimizes the overall deviation from these objectives.

A final issue in developing evaluation criteria is the sensitivity of the criteria to changes in resource allocations. Are these criteria fairly robust with respect to small changes in data, or are they sensitive functions whose values can change dramatically in response to only small changes in solution variables? This question is particularly important when there are multiple criteria and objectives and we seek to develop a wide variety of acceptable alternatives. Also, all of the resource allocation models developed to date appear to devote far too little effort to exploring the models' sensitivities to various errors and probabilistic variations in the model parameters.

B. Research Needs for Resource Allocation Decisions

1. Federal Level

Research is needed at the Federal level to address many resource allocation issues. These issues include determining what is an appropriate allocation of funds for direct care, indirect care, and research. What are appropriate payment mechanisms? Can Federal guidelines be developed for allocating services, treatment modalities, facility capacities, and program priorities? Can we develop widely acceptable standardized patient-classification schemes with respect to type of emotional or functional disability and degree of illness? Given the variety and complexity of resource allocation decisions, at which level of the hierarchy is each type of decision most appropriately made? The use of mathematical programing models is appropriate to answer some of these questions.

In the development of health manpower, the trend appears to be toward more and more specialized manpower categories. Is this an effective use of resources with respect to training and allocation? There is clearly a problem with maldistribution of mental health care similar to that experienced in the general health care system. Does the growing number of specialists exacerbate the maldistribution in the same way that it does in the general health care system? Use of a simulation model might enable us to explore the potential impact of alternative manpower development plans.

A primary area of current Federal involvement is prevention of disease and promotion of health. Not all mental health disabilities are amenable to prevention. Only those illnesses and disabilities for which the etiology is well understood are immediate candidates for resource allocation in prevention. High priority research items include determining which other illnesses and disabilities are amenable to prevention or intensive study.

One example of resource allocation for prevention of mental disability is the provision of services to those who are developmentally disabled. The usual causes of developmental disability include mental retardation, cerebral palsy, epilepsy, and autism. The greatest potential for cost-effective resource allocation for these disabilities lies in the area of prevention. Because low birthweight consistently correlates with these disabilities (e.g., mental retardation, cerebral palsy, low IQ scores, neurological impairment, epilepsy, subnormal development and psychological disturbances, and autism) and because low birthweight is a surmountable problem in many instances, support for a program to reduce the occurrence of low birthweight could be an effective use of resources in preventing developmental disability.

Moreover, the lower the birthweight, the greater the incidence and severity of these maladies. Information is being collected in WIC (the Woman, Infant, and Children supplemental food program sponsored by the U.S. Department of Agriculture), which has great potential as a data base for good resource allocation modeling in the future. At the Operations Research Laboratory, University of Illinois, we are developing some preliminary models to aid decisionmakers at both the State and regional levels improve resource allocation to such programs. To develop better models describing the relationships between good nutrition and long-range health and mental health status, however, requires extensive research. NIMH should cooperate with the Department of Agriculture in developing long-range tracking and evaluation programs for the infants aided by the WIC program.

A variety of data bases have been developed through Federal efforts but are not used effectively for resource allocation decisions. Results of surveys are available from the NIMH National Reporting Program, the Client-Oriented

Data Process, the National Drug Abuse Treatment Survey, the Financial Management Information System, and the Drug Abuse Warning Network from the National Institute on Drug Abuse, as well as the National Alcoholism Program Information System and the State Alcoholism Profile Information System maintained by the National Institute on Alcohol Abuse and Alcoholism. Operations researchers need to be informed of the allowed access to these data bases, and research needs to be done on how to effectively integrate these data into resource allocation decisions by means of information retrieval systems and data management models.

Different types of information might serve as input for decisionmaking: real-time values, forecast variable values, and historical variable values. In short-term decisionmaking, as opposed to long-term decisionmaking, different mixes of these types of information are appropriate. Research is needed to determine which data should be used for which decisions.

The Mental Health Demographic Profile System developed by NIMH also needs to be integrated into health planning and resource allocation. Defining populations at risk is only the first step. Determining the types of mental disabilities for which these populations are at risk and their susceptability to intervention must precede effective resource allocation.

The NIMH National Reporting Program periodically inventories various components of the mental health care delivery systems, including general hospital psychiatric services, comprehensive community residential programs, psychiatric halfway houses and community residential programs, psychiatric hospitals, and various other institutions. Included among the data collected are type of services provided, caseload, staffing patterns, expenditures, and, in some cases, characteristics of clients admitted, both demographic (age, sex, race, income, etc.) and treatment-related (diagnosis, services and treatments received, length of stay, source of payments, etc.). These data provide a measure of the allocation of resources; however, the efficacy of the resource allocation in terms of patient outcomes has not been included in the data.

As health service modelers, we are forever having to use proxy measures, because the measures we would like to use are not available. We can observe area populations over time, and, using proxy measures of mental health, we can in theory follow the corresponding changes in the populations' mental health as a function of the differing mental health services being provided. There are complications, however, because many providers of mental health care services are not currently being surveyed. If we could collect all these additional data, it is still unlikely that we could distinguish differences in population response because of the large variances in response to alternative treatments.

Developing resource allocation models based on these data has potential nevertheless. If we can develop for some relatively isolated geographic areas an inventory of all or a majority of the mental health services provided as defined from staffing resource allocation, if for each program we have relatively complete data on the socioeconomic and health characteristics of the clients, if we have available for the same population a variety of proxy measures for mental health status, and if we have collected these measures for a sufficiently long period of time, then we ought to be able to build a variety of predictive regression models.

A particularly urgent research project is the collection and joint evaluation of the mental health components of the health systems plans developed over the past several years by more than 200 health systems agencies across the country. Because each agency was mandated to develop plans that extend into developing recommendations for the allocation of resources, and because each is on the "front line" with respect to understanding the special needs and characteristics of its own area, a study of these plans should provide us with a rich set of resource allocation alternatives.

2. State Level

A primary resource allocation consideration at the State level has emerged because of the utilization trends in State mental health facilities. Between 1955 and 1975, the number of residents in State and county hospitals has fallen from 559,000 to 191,000. The locus of care clearly has shifted from the State and in-hospital treatment to outpatient programs within local communities. Responsibility for inpatient psychiatric acute care is being assumed by psychiatric units within general hospitals, and the number of federally funded community mental health centers and nursing homes accepting mentally ill patients has grown. Associated resource allocation questions arise. Are these trends resulting in the most appropriate use of facilities and personnel (Taube et al. 1978)? Are there predictable ways in which the financing of the health care delivery system--for example, splitting the costs between State, county, and local community--can affect the appropriateness of the care (Bodin et al. 1972; Bodin and Carroll 1974)?

Among the more interesting resource management schemes to be tried on a statewide basis is SCOPE (staffing care of patients effectively; Naleway 1970), a computerized technique for determining treatment staffing requirements in State mental hospitals. To implement SCOPE, data must be collected on the needs and characteristics of each patient, on the residential units in which they are housed, and also on the authorized treatment staffing assignments. Analysis of these data for the hospitals in an entire state (Pennsylvania) resulted in the construction of a profile of the staffing needs of the residential service system.

A natural research idea emerges from the fact that these data exist. Surely a variety of models could be constructed for which the output variable is the patient's progress, the controllable variables are the staffing types, and the uncontrollable variables are, to some extent, the other patient characteristics.

3. Regional Level

A mixture of decisions establishing the allocation of money and other resources that directly affect an individual's treatment exist at the regional level. Two major agencies are involved in decisionmaking on the regional level: the Health Systems Agencies boards and the Mental Health 708 boards. Requests for facility and program location and expansion initially seek approval at this level. Regional planners face the need to determine the most appropriate area-specific mixes of inpatient (acute and long-term) and outpatient facilities. Among unanswered questions are the following: How should these mixes vary depending upon population characteristics? What is the impact of recidivism, and how can we incorporate recidivism considerations into resource allocation models? Markov models of recidivism and computer simulations of population responses might be useful adjuncts to mathematical programing models at this level of planning.

4. Local Level

Resource allocation decisions at the local level are made within all facilities and programs in order to support many types of functions. These functions include determining the need for such services as growth-related activities for enhancing the client's intellectual, interpersonal, and daily living skills; maintenance-related activities; case management; prevention of disease; general health promotion or restoration; ancillary and administrative services; research; program evaluation; and staff development.

These functions could be carried out in a variety of settings: protective (e.g., mental health hospitals and acute psychiatric units in general hospitals), supportive (e.g., sheltered workshops, private psychiatrists' offices, and mental health centers), and the natural environment (e.g., clients' homes and places of employment). Natural questions that emerge are, Where should these services be located? Who should be providing them? How much of each should be available?

Even though resource allocation models have been developed for some particular types of agencies and programs, they rarely have had much impact on the resource allocation processes. For example, a variety of decisionmaking models have been discussed for planning drug abuse control programs (Correa and Sangl 1977). What is missing from the evaluation, however, is how these models can be integrated into existing decisionmaking processes. Case studies are needed to see whether any of these models, or modifications of them, can actually be implemented into ongoing program management.

A paper by Hayes-Roth et al. (1977) illustrates prior research into the decisionmaking process within a mental hospital. The authors of that paper explore not only the sequence and interrelationship of patient-related decisions but also the information flow requirements. Exactly this kind of detailed inquiry into the decisionmaking process needs to be conducted for other components of the mental health service system at all levels, local through Federal.

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The timing of resource allocation is also of interest. As Burgess (1974) found in Illinois, it may be advisable to concentrate the allocation of resources on those individuals most at risk, specifically those in their first year after release from residential treatment centers.

With respect to selecting treatments for patients, the utilization of decision tree analysis and Markov chain models appears to be appropriate. The state of an individual's mental health in these instances can be modeled as responding or not responding to various treatments.

V. SUMMARY AND ADDITIONAL RECOMMENDATIONS

What has been missing to date from the use of operations research in the mental health service system is a clear understanding of which decisions are important (with respect to either dollars or impact), who the decisionmakers are, what the criteria and objectives controlling their decisions are, and what types of models best support these decisionmaking processes. To aid decisionmaking, we must develop easy-to-use interactive computer programs that automatically access appropriate data bases, produce useful management information, flag potential problem areas, and make recommendations for resource allocation.

There is a trend toward the development of such programs by information and computer system specialists. These specialists may not be sufficiently familiar with decisionmaking processes to design the most useful content and packaging of the information. Mental health specialists, on the other hand, may not be fully aware of the latest technology for developing information systems and decision-aiding models. Funding interdisciplinary teams (operations research, computer science, and mental health specialists) to develop working information management systems is important.

One aspect of decisionmaking that needs additional investigation is the fact that decisions are usually triggered by events, and this triggering process can be used to advantage. To do this, however, the following issues must be clarified: What proportion of the resource allocation decisions are made with predictable timing and in response to regularly recurring events? What proportion of the total amount of resources in mental health is allocated in a predictably timed manner?

Accordingly, the author urges support of research to accomplish the following objectives:

1. Map the existing flow of resources through the mental health service system hierarchy. Determine which types of decisions allocate the greatest proportion of funds and which have the greatest potential for health impact.

2. For all categories of mental illness and disability, develop and evaluate

   - a. Methodologies to estimate total lifetime costs;
   - b. Treatment benefit measures;
   - c. Recidivism models;
   - d. Patient classifications;
   - e. Potential for disease prevention;
   - f. Models of patient programs as a function of resource allocation; and
   - g. Optimal timing of resource allocation.

3. For all settings and levels of the hierarchy, develop and evaluate
   - a. Planning models;
   - b. Resource allocation models;
   - c. Information retrieval and data management systems; and
   - d. Implementation strategies.

4. For all existing and potential data bases, evaluate
   - a. Potential for contributing to the development of descriptive models; and
   - b. Potential for contributing to decisionmaking.

The process of allocating resources is continuous, and there are always alternative allocation possibilities from which choices must be made. The support of a research program to study and improve this resource allocation process for the mental health service system is important.

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Chapter 4.

OPERATIONS RESEARCH AND MENTAL HEALTH SERVICES RESEARCH: LARGE-SCALE SYSTEMS INTERACTIONS

Dean H. Kropp, Ph.D.

I. INTRODUCTION

Current studies estimate that a substantial portion of the U.S. population, about 15 percent, is affected by mental disorders within any 1-year period (Taube et al. 1978). Consequently, such mental disorders represent a major U.S. health problem that cannot be ignored. Indeed, in recent years considerable attention has been focused on Federal and State efforts to deal with the problem.

A major task facing U.S. health planners is how to conceptualize, organize, and operate a mental health care system that can effectively provide the full range of services the Nation requires. To accomplish these comprehensive goals, it is imperative that the health planning efforts emphasize the importance of increasing interaction and interdependence among governmental agencies, other service organizations, and the population. Since formal planning groups have only recently started to consider these interactions, the growing emphasis on such interactions will probably produce the need for fundamental changes in future approaches to planning.

The purpose of this paper is to examine these interactions and the interdependencies of large-scale systems and to identify how the techniques of operations research can be used to improve our understanding of them. Section II reviews several current trends and issues related to health care services in the United States that are important to future planning. Section III uses the systems dynamics paradigm to identify the systems that must be considered and to define their characteristic elements. Section IV discusses how operations research methodologies might be of general use in characterizing these large-scale interactions. Finally, section V describes several applications of these methodologies that warrant immediate research attention.

II. IMPORTANT TRENDS AND ISSUES FOR U.S. HEALTH CARE SERVICES

The U.S. mental health service "system" is in fact not one system but a loosely organized grouping of many systems. Over the past decade, numerous changes have been made in this system in an attempt to make it responsive to those who need care while at the same time reducing its cost.

The following discussion demonstrates the extent of the problems facing health care planners and the need to consider the interactions of the systems. Although these interactions between various systems are extremely complex, they fall into the three basic categories: resources, population, and environment.

The resource interactions represent the financial flows between systems, such as from Federal, State, and local funding organizations, to the agencies providing care. Such interactions are important because they make the provision of mental health care possible.

The population interactions include patients' characteristics as well as the flows of patients between systems. The individuals of interest to mental health planners possess certain functional characteristics, including medical, behavioral, and psychosocial characteristics. (In the language of operations research, such characteristics can be represented by "state variables" in probabilistic analyses.) The characteristics are important to the examination of systems interactions because they combine with the number of clients to determine the needs of various programs. They influence individuals' responses to programs and, therefore, influence client outcomes. As people move into, through, and out of various mental health and other programs, they create a service history that further defines their functional characteristics.

The environmental interactions involve the intersystem flows that affect the adequacy and effectiveness of various programs. One such environmental interaction involves the service providers--the human capital of the various systems. Certainly, the number of providers and their skills affect the quality of an individual system or program. However, the supply of and the demand for providers in each of the various systems interact to determine the actual utilization of personnel. A second type of environmental interaction affects the systems in the area of policies. Such policies, represented by decisions made both in the systems themselves and in governmental agencies, have important effects in governing the rate of flow of resources, patients, and providers from one system to another. Through the governmental regulatory process, the policy interactions control the level of functioning of the various systems.

A. Recent Trends

Given this general description of the basic types of interactions essential to the mental health service system, we can start to describe the recent trends that have affected the delivery of mental health care. These trends can be grouped into the areas of (1) structural delivery system changes, (2) demographic shifts, (3) social problem shifts, (4) attitude shifts in the general population, and (5) public policy priorities for cost-containment. Table 3 summarizes the trends.

In the U.S. mental health service system, there are four major sectors in which mental health services are provided: (1) the specialty mental health sector, which encompasses a wide range of facilities, including State and county mental hospitals, private mental hospitals, hospitals with psychiatric units, community mental health centers, private practice psychiatrists and psychologists, and residential mental treatment centers; (2) the general hospital inpatient and nursing home sector, which contains general hospital inpatient facilities, general hospitals without psychiatric units, and nursing

Table 3. Important recent trends for U.S. health care services

STRUCTURAL DELIVERY SYSTEM CHANGES

Long-term to short-term
Inpatient to community-based
Increase in general hospital beds
Increase in third-party coverage

DEMOGRAPHIC SHIFTS

Increase in percent and number of aged
Increase in high-risk adolescents

SOCIAL PROBLEM SHIFTS

Increase in crime rate
Increase in alcohol and drug use rate
Increase in divorce rate and family fragmentation

ATTITUDE SHIFTS IN GENERAL POPULATION

Increase in acceptance of mental illness
Increase in interest in informal self-help systems

COST-CONTAINMENT PRIORITY IN PUBLIC POLICY

Increase in emphasis on cost, access, and quality
Increase in estimates of economic burden of mental illness

homes; (3) the primary care and outpatient medical sector, which includes office-based physicians, health department clinics, general hospital outpatient clinics, and hospital emergency rooms; and (4) the not-in-treatment and other human services sector, which includes individuals whose mental disorders are not detected and those who do not receive treatment in the health care system.

Sectors (2) and (3) often are collectively referred to as the general medical sector (Regier et al. 1978). Many of the important trends and issues in mental health today involve the changing roles of these sectors.

Most Americans with mental disorders now receive care from either the specialty mental health sector or the general medical sector. The locus of treatment is shifting so that about one-fifth of patient episodes occur in the specialty mental health sector and about three-fifths occur in the general medical sector. About one-fifth of those with mental disorders receive no treatment or receive it from family service agencies, religious counselors, and other social welfare agencies outside the medical arena (Regier et al. 1978).

The specialty mental health service system formerly was characterizered by provision of long-term inpatient care in public facilities. Now, however, it is oriented more toward short-term and outpatient care in the private sector. As a result, the length of stay and number of inpatient beds in specialty mental health service system facilities has dropped significantly.

The increasing importance of the private sector is shown by the fact that the number of people seen in private settings represents approximately half the people under treatment in all organized mental health settings (Taube et al. 1978). Such a change is important because it may involve and, indeed, require different ways of providing for and controlling the financial resources allocated to mental health care. In addition, this change from inpatient to outpatient care may affect other systems by altering the functional characteristics of the patients flowing into the systems.

The primary locus of care for the mentally ill has shifted from State and county mental hospitals to facilities located in the community, particularly to community mental health centers and to other agencies providing outpatient psychiatric services (Kramer 1977). In addition, nursing homes and psychiatric inpatient units of general hospitals have become more important. State and county mental hospitals formerly tended to be self-sufficient units isolated from society. The shift to community facilities has an important effect, because they are more prone to interact with other social systems.

The provision of facilities for aging people who are no longer able to care for themselves has become one of the fastest growing private industries of recent years. Indeed, there is a current trend toward multiple-facility organizations that are parent or holding organizations (Earle 1970). Although the stock market performance of these corporations has been spectacular, they are not exempt from mismanagement, corruption, and collapse (New York Times 1973). In addition, the professionals, paraprofessionals, and caretakers clustering around these facilities have become an ever-expanding group; many of them are inadequately prepared to work with the elderly (Freed 1977).

Many changes have occurred in the areas of mental health care financing. The Social Security Amendments of 1965 established national programs of health insurance (Medicare) for the aged and medical assistance payments (Medicaid) for those who cannot afford medical care. Both programs included a limited set of mental health benefits. Private health insurance policies also have had provisions that discriminate against mental disorders as compared with other disorders. Group coverage, however, now is exhibiting a tendency toward providing comparable benefits for hospitalization for mental illness. The principal problems now occur in the area of outpatient psychiatric care, where exclusions and limitations are still common (Kramer 1977). In the future, the enactment of some form of national health insurance may remove completely the funding restrictions on coverage of mental health services. Such changes are important because of their potential effects on the flow of financial resources into the various systems.

Many factors have combined to increase the number of persons subject to the risk of institutionalization. For example, improved medical care, health, and social services have prolonged the lives of many persons and have produced a large population of individuals who require long-term care in homes for the aged and dependent. Indeed, the largest proportion (44 percent) of people now in institutions is in such homes. The projected need for such facilities, personnel to staff them, and funds for their operation, therefore, will increase sharply (Kramer 1977). Such needs, which involve the basic types of system interactions, may well place a heavy burden on the various systems.

The post-World War II baby boom of the 1950s has also had its effect. These children have entered or soon will enter the 18-to-34 age group, in which the incidence of conditions requiring institutionalization is high. This age group is a high-risk group for schizophrenia, which frequently requires admission to a mental hospital. Further, it is a high-risk group for arrests for crimes of violence, burglary, and other types of offenses that may lead to prison sentences (Kramer 1977). As a result, the set of basic patient characteristics must be enlarged to permit descriptions of patients with multiple problems.

The U.S. criminal justice system is subject to growing pressures. Since the 1960s, there has been a documented increase in the number of crimes committed in the United States each year, and expansion in the correctional system is not keeping pace with the increase in crimes. As a result, overcrowding in correctional institutions has become a national problem. The possible court-mandated reduction in the prison population and reductions in length of prison terms may well lead to even greater increases in the crime rate and to the presence in society of more individuals having psychiatric morbidity. If such changes occur, they will present problems for many systems, because the clients of the criminal justice system will increasingly become patients in the mental health system.

Racial and cultural minority groups are unevenly represented within various mental health service settings. Although the admission rates of minority group members are increasing in several settings where they previously were quite low, such as in psychiatric units of general hospitals and in private psychiatric hospitals, large differences in admission rates still exist (Taube et al. 1978).

In addition to the above changes, there have been other important shifts in the social problem area. First, the substance-abuse rate appears to be increasing, especially among adolescents. Second, family-related problems, including divorce, are growing. Both kinds of problems can increase the number of people requiring mental health treatment institutionalization.

Another important trend relates to the attitude shifts of the general population. Although there is still a social stigma attached to mental illness, the 1970s saw growing public acceptance of its existence. Further, self-help philosophies (such as Ehrhard's E.S.T.) enjoy growing popularity. As a result, it is conceivable that individuals who formerly attempted to conceal their problems are placing demands on the mental health service system.

Finally, the mental health system has to deal with the high and still growing emphasis on cost-containment articulated in the public policy arena. Given current estimates of the great economic burden imposed by mental illness in general and by certain diseases, such as alcoholism, in particular, public emphasis on the cost and quality of and access to health care will insure that mental health programs will receive a great deal of scrutiny.

These changes in public demands on and expectations of mental health programs result from a variety of factors, including social legislation, new discoveries of treatment of diseases, demographic changes, increasing cost of care, social conditions and problems, discriminatory practices, inadequate community programs, and inappropriate living arrangements for the aged, disabled, or mentally ill (Kramer 1977). This paper is not intended to examine these factors in depth, but to consider how these changes affect the planning process.

B. Major Issues

Mental health planners must consider these changes in detail if they are to deal effectively with major questions related to deinstitutionalization, the increasing interactions between the mental health system and the general health care system, and the changing composition of the population using mental health services. The following discussion examines these questions.

We know that many people have been moved from locked wards in hospitals to living arrangements in the community. Many of these people, however, are in nursing homes or boarding houses that often promote neither achievement of greater independence nor participation in activities that approximate normal, everyday life. In addition, although expenditures for State and Federal hospitals have dropped, they have not always been reduced in proportion to declines in the inpatient census. Current estimates of the cost to continue to provide such community-based care and care in nursing home facilities continue to rise, fueled by such factors as inflation, labor laws, rising expectations of those who have made careers by staffing such programs, and pressures to serve a larger number of disturbed people. Given these concerns and problems, all available alternatives must be examined to determine methods that are both cost-effective and client-effective in locating these deinstitutionalized patients.

Today, many individuals with mental disorders are identified in the general health care system, especially in the primary care or outpatient areas. Given the growing availability and use of such facilities, it is probable that in the future more and more psychiatric morbidity will be diagnosed. This situation also indicates a need to define psychiatric morbidity more clearly.

Before doing more to encourage this shift from the mental health system to the general health system, it is necessary to determine if the general approach of diagnosing and treating mental disease in the general health care sector or other social service sectors is cost-effective. Further, if this general approach is cost-effective, then the most effective specific methods of diagnosis and treatment must be identified.

Kramer (1977) made projections of inmates of the different types of institutions, but took into account expected changes only in the various age, sex, and racial groups. Further, his study appears to have considered each problem in isolation. Kramer admits that increases in the use of mental health facilities, in the incidence and prevalence of mental disorders, and in the rates of imprisonment and duration of prison sentences would alter his projections considerably.

There is now evidence that such changes may be taking place. For example, the federally assisted community mental health centers are providing a wide array of services and, as a result, are causing increases in the use of mental health facilities. Further, in response to the problems of overcrowding in correctional institutions, courts are starting to order reductions in the prison population. As a result, there is now an even greater need to explore the estimated impact of these changes to achieve an updated overview of the problem. Given the nature both of the current trends in U.S. health care and of the major problems that must be faced, it is clear that any future planning efforts must consider the large-scale interactions between the mental health service system and the other service systems.

III. A CONCEPTUAL MODEL OF LARGE-SCALE SYSTEM INTERACTIONS

Given the need to examine the large-scale interactions between the mental health service system and other service systems, the approach that immediately suggests itself is the systems dynamics methodology developed and advocated by Jay Forrester (1961; 1968; 1969) and others. The scale of the interactions we are considering is similar to that of the interactions of population, resources, and the environment. In a well-known study, systems dynamics became the basis of the Club of Rome report, often called "Limits to Growth" (Meadows et al. 1972). With this precedent, the systems dynamics methodology could well be of use in examining the U.S. mental health service system and its important interactions.

Rather than going to the extreme of specifying a very detailed model, this paper is realistic about what can be achieved with a modeling effort. Even with unlimited resources, there are limits to what can be achieved with such a large-scale model. Consequently, this paper presents only the philosophy of systems dynamics and shows how it can be applied to the mental health system and other systems with which it interacts. In particular, this paper presents a descriptive model of the systems with which we are concerned to identify the important system elements and raise questions to provide a more structured starting point for an analysis.

The immediate goal of this quasi-systems dynamics modeling effort is to create a situational model that can help us gain more knowledge about the mental health service system and its important interactions. Such a model will (1) identify the most critical system components, and (2) reveal many of the variables pertinent to the situation.

The situational model assumes that the provision of mental health services is an interactive, time-varying process taking place in a changing environment. This environment includes the forces acting on the population of individuals who are potential clients of the mental health service system. Many pressures come to bear on the population, and some individuals will be affected to the point of needing, but not necessarily receiving, care. These pressures include social tolerance of deviance, inadequate public health, economic pressures, family stress, and employment pressures. In addition, the environment contains other important processes, such as those relating to illness, genetic factors, and sociodemographic characteristics. Of course, one of the difficulties of the modeling process is that it is very hard (and in some cases impossible) to model some of these processes. As a result, some aspects of the overall systems dynamics model of the interactions between the mental health service system and other systems may be extremely vague, even when only qualitative descriptions are attempted.

The mental health service system can be thought of as interacting with the environment and four other systems: general health care, other social services, criminal justice, and sources of financing. Each system contains its own important components or elements and the variables that determine how that system functions. However, the operation of each system is also affected by variables in other systems. These variables account for the interactions and interdependencies among systems.

A. Specialty Mental Health

The U.S. specialty mental health system is so complex that it is necessary to examine it from two different perspectives--one macroscopic and one microscopic.

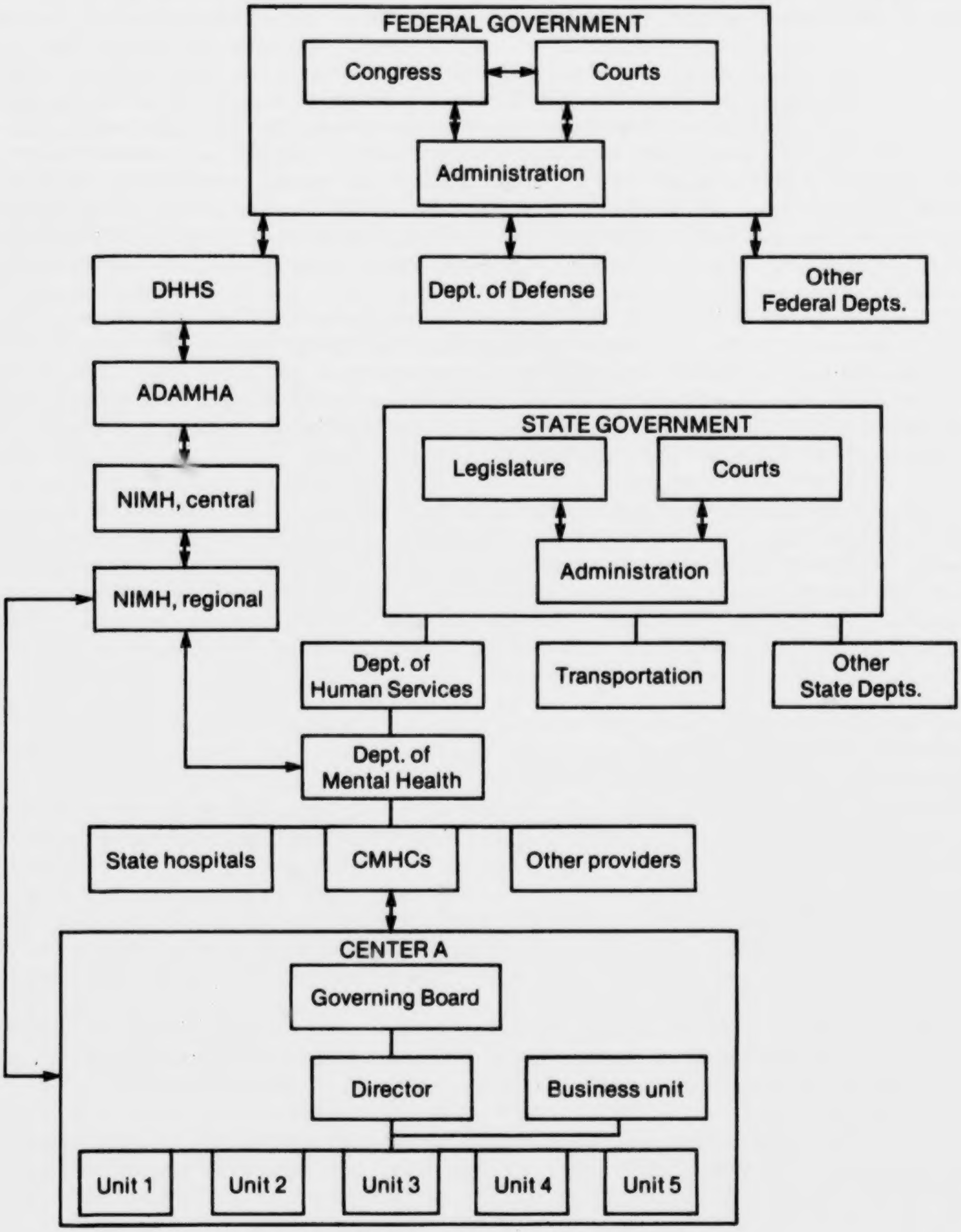
On a macroscopic level, Kilburg's (1977) analysis proves extremely helpful. Figure 9 diagrams the major structural elements of the specialty mental health system in a hierarchical fashion. There are also many minor elements of this system that will be discussed later. All the elements in the figure can be thought of as systems, because every level in the mental health system is affected by the environment. The major linkages depicted in the figure run between the major components and the administration on each level.

Within the Federal Government, it is possible to detail interactions between Congress, the Federal court system, and the Administration with respect to the mental health system. Most important are the environmental policy interactions concerning (1) the passage of various pieces of legislation affecting mental health, (2) the role of the Federal courts in interpreting and

FIGURE 9

Environment

(the various States and territories of the United States, their people, and their systems)


FEDERAL GOVERNMENT
Congress
Courts
Administration
DHHS
Dept. of Defense
Other Federal Depts.
ADAMHA
NIMH, central
NIMH, regional
STATE GOVERNMENT
Legislature
Courts
Administration
Dept. of Human Services
Transportation
Other State Depts.
Dept. of Mental Health
State hospitals
CMHCs
Other providers
CENTER A
Governing Board
Director
Business unit
Unit 1
Unit 2
Unit 3
Unit 4
Unit 5

Structure of the specialty mental health system

SOURCE: Adapted from Kilburg 1977.

enforcing the laws, and (3) the role of the Administration in implementing the laws and undertaking regulatory actions.

State government is the second level in the figure. Its major elements are the State legislature, the State courts, and the State administration. The operation of this level is similar to that of the first level.

Finally, on the local level, we can examine a typical unit actually providing care, such as a community mental health center, here called Center A. Its major elements are a governing board, a director, and a set of clinical and business units. This center interacts with the State government through its department of mental health and with the Federal Government through its regional offices. Such interactions frequently involve resources or policies or both. These are not the only possible or existing interactions between the local center and the two systems above it. We can learn more about these local interactions from a microscopic perspective.

At the microscopic level, in addition to the previously mentioned community mental health centers, are State and county mental hospitals, other public mental hospitals, private mental hospitals, residential treatment centers, halfway houses, and homes for the aged, dependent, or mentally retarded.

There are several important variables on this level. These variables include the current census or utilization rate of the facilities, changes in census or utilization rates, costs per unit of treatment, and the effectiveness of alternative treatments in terms of changes the treatments produce in the functional characteristics of clients. In addition, we must consider the numbers, changes in numbers, and capabilities of the system's providers. These considerations are important to the extent that they affect the population of clients who move from one system to another.

That each system component is itself a complex system composed of interacting subsystems further complicates the modeling process on the microscopic level. For example, Center A, a typical community mental health center, has goals, funding, and reimbursement plans that have been defined by the Federal and State governments in the forms of laws, rules, and regulations. These mandates control not only the services that the center offers but also the center's organizational structure, the populations that should be served, and the center's processes of financial management.

The typical center is charged with the responsibility of serving an artificially defined catchment area. This area can itself be defined as an uncontrolled, active system. Often it contains from 75,000 to 250,000 individuals and an unidentified number of organizations such as churches, schools, social service organizations, social organizations, and businesses.

B. General Health Care

On a microscopic level, we find the following typical components of the general health care system: general hospitals with psychiatric clinics or inpatient psychiatric units, general hospitals without such clinics or units, freestanding outpatient clinics, health maintenance organizations, long-term medical care facilities, other practice arrangements such as individual or group practices, and finally, the providers employed in the system.

Many of the important variables in this system are identical to those described for the mental health care system and therefore are not described here. It is also important, however, to describe the rate of transfer of clients from the general health care system to the mental health care system and back again. This rate usually is controlled by psychiatric referrals. As stated previously, this variable defines an important element, the population, that provides a vehicle for the interaction between systems.

In addition, it is necessary to be concerned about the effectiveness of the programs and, in particular, about the capability of the providers of general health care to recognize, diagnose, and treat psychiatric disorders. Because the general health care system in many ways competes with the specialty mental health system for financial resources and providers, these other concerns relate to the resource and environmental interactions between systems.

C. Other Care Providers

Under the heading of other care providers, we include homes and schools for the mentally retarded, homes and schools for the physically handicapped, homes for dependent and neglected children, homes for unwed mothers, vocational rehabilitation services, and services related to alcohol and drug abuse. The last of these services include detoxification units, civil commitment units, alcoholism clinics, transitional facilities, occupational programs, and programs such as Alcoholics Anonymous. This system is similar to the mental health service system and has many of the same important variables. As with the general health care system, the important aspect of this system of other care providers is how it affects the functional characteristics of the population that moves into another system.

D. Criminal Justice

The criminal justice system includes law enforcement agencies, courts, correctional institutions, and rehabilitation programs. The variables that determine the functioning of this system and thus affect its interactions with other systems include crime rates, arrest rates, conviction rates, incarceration rates, and rehabilitation rates. Such variables affect both the number of individuals in the population who may require mental health services and their characteristics.

E. Sources of Financing

The major components of the system comprising sources of funds include groups providing public funding (such as Federal, State, and local governments), those providing private funding (such as businesses and insurance companies), and, finally, the individuals themselves. Here, the important variables describe the amount and nature of the funds or resources provided to the many programs. These resources determine the level of operation of the programs and, in some cases, even the overall possibility of providing services. It is also necessary here to consider the means for funding of mental health services versus general health services and for varying scales of payment by the individuals receiving treatment.

IV. USEFUL OPERATIONS RESEARCH METHODOLOGIES AND APPROACHES

It should be noted that the conceptual systems dynamics model is not novel. More than 10 years ago, both Flagle (1966) and Horvath (1966) proposed the use of simulation models as a first step toward understanding the complex interrelationships of the national health care systems. Early in the 1970s, the Institute of Medicine, National Academy of Sciences, explored the feasibility of developing simulation models to provide a framework for discussing and assessing the benefits and costs of proposed programs for national health insurance (Sheldon 1975). In all cases, however, the unfortunate fact is that the actual simulation models were not developed. It remains to be demonstrated whether this failing will be repeated in the future.

It is not possible now to add a great deal of detail to the overall systems dynamics model, but, for several reasons, it may not be necessary to do so.

First, the information base on which such a model is built is an essential element of formal planning activities, especially because policy decisions must be predicated on the anticipated responses of the system. In many instances, however, available data are inadequate for dealing with the key interactions discussed in section III. For example, very little epidemiological information is available about the relationship between mental disorders and other diseases, crime, poverty, juvenile delinquency, illegitimacy, educational disabilities, and other social problems, including racism, conditions in the ghetto, and lack of opportunity. Little is known about the employment of physically and mentally handicapped persons who have been rehabilitated. Without such data, it is impossible to complete a detailed specification of the systems dynamics model, and it would be difficult, if not impossible, to include political processes and administrative actions in such a model.

It is not certain, however, whether efforts to add so much detail to the model would be consistent with a reasonable modeling philosophy. It could be argued that one of the major benefits of the Club of Rome report was the identification of the scope of worldwide problems with regard to population, resources, and environment over the next century. Looking back to section II, we are already aware of the scope of the problems facing the U.S. mental health service system.

Another goal of building such a large-scale model is to identify the systems, their major components, and the variables involved in these problems. Section III has presented a preliminary attempt to meet this goal. As a result, it could well be argued that future efforts should not proceed on a macrolevel because of the seemingly large costs involved and the limited benefits to be achieved. Indeed, it may be wiser to investigate other areas first, such as those discussed elsewhere in this volume--modeling need, demand, utilization, program evaluation, and resource allocation.

It seems ill-advised, however, to ignore completely the large-scale interactions, because they have important implications for the success of these other efforts. A compromise position is in order. The author advocates a parallel approach that would respond to Kramer's call for efforts to narrow the gaps between available knowledge and that which is needed (Kramer 1977) and that would use operations research methodologies to deal with subsystems of the larger problem. This parallel approach would develop our understanding of the mental health service system and would make it possible to consider more large-scale models in the future.

Before examining specific operations research methodologies that can be employed in this approach, it is wise to consider how these methods should be used. In particular, it will be helpful to focus on the mental health service system as a decision system.

A good example (provided by Dr. Christopher Dunn of NIMH) of the potential benefits of this approach comes from the criminal justice system. The original model of this system examined the stocks and flows in Allegheny County (Pittsburgh), Pennsylvania. By changing these stocks and flows to examine the effects of various decisions relating to rates of arrest, prosecution, and conviction, investigators were able to provide a good idea of interactions at a microscopic level. Using this view of the system as a set of decisions, investigators focused research attention on the processes and criteria of decisionmaking. They found that such a focus helped them increase their understanding of the forces causing change.

In criminal justice system research, extensive work has been performed since these early modeling efforts. One reviewer (Chaiken et al. 1976) has identified 60 models that at one time or another were used for supporting decisionmaking in the criminal justice system. Decision models are now available and being used as aids in making decisions about criminal case investigation, release on recognizance, bail, prosecutorial case selection, sentencing, and parole.

One set of parole guideline models, for example, is useful in approximately 75 percent of the cases coming before the U.S. Parole Commission. Thus, it frees the decisionmakers to concentrate on the 25 percent of cases that the parole guideline models cannot handle because the probability of error is so great. In that 25 percent of cases, the four or five criteria upon which the models were based do not provide sufficient information for decisionmakers. This means that the decisionmakers have to strive to develop the additional information needed to help them make good decisions.

In a time of constrained resources and increased demands for accountability, the appeal of models like those of the U.S. Parole Commission is very high. Such approaches are not without their critics, however, particularly when applied in the areas of human behavior that seem to be highly judgmental. Nevertheless, mental health professionals are often called on to make evaluations analogous to those involving sentencing or parole. Mental health decision support models that could be used in the majority of the decisionmaking situations might be of great assistance in allowing mental health professionals to concentrate on the more difficult minority of decisions about delivery of services and about the best courses of treatment.

In addition to providing aids to decisionmaking, operations research methods can be extremely helpful in defining the systems themselves. In mental health planning, it will be essential to determine the set of independent variables--that is, patient attributes--that predict resource consumption. Without such information it will be difficult to define even the decisionmaking situations themselves.

Thus, the best use of operations research methods appears to be in providing aids to decisionmaking and increased understanding of the systems themselves. In such a vein, several approaches can be used, including small-scale simulation models, optimization models, and combination optimization-simulation models.

Small-scale systems dynamics simulation models have been used to examine some of the interactions between the mental health system and other systems. These models are useful because they examine small problems and thus have reduced information requirements. Typical applications of this simulation approach include Hertzman and Levin's models of the mental hospitalization process, exploring the effect of fluctuating admission and discharge rates on workload and morale (Hertzman and Levin 1974a, 1974b); Levin and Roberts' examination of the treatment dropout process in a community mental health center (Levin and Roberts 1976); Bernard's view of the distribution of services to mentally deficient children (Bernard et al. 1977); Levin, Hirsh, and Roberts' examination of a narcotics addition epidemic in a community (Levin et al. 1972; Levin et al. 1975); and Holder's study of an area-wide alcoholism treatment program (Holder et al. 1970; Holder and Kennedy 1971).

These models have had a moderate degree of success, because they have provided a structural framework for analysis of problems and because they have identified useful programs and policies that otherwise might have been ignored. Because of these successes, such small-scale simulation models probably will see increased use, especially when more and more data become available.

One of the failings of simulation is that it is a descriptive technique. Certainly the descriptive ability of simulation is attractive because it permits analysts to describe complex relationships and to provide realistic models having great richness of detail. However, the costs of simulation can be very high. In addition, because simulation is not an optimizing method, it may be necessary for investigators to examine many alternatives without any assurance that they are approaching an optimum solution. In mental health planning, this lack of optimizing ability of simulation models can be a problem.

Accordingly, optimization models, in addition to simulation models, can be useful in examining the interactions between systems. Optimization models have been used to examine the policies of deinstitutionalization, for example, and to examine the needs for planning drug abuse control programs (Correa and Sangl 1977).

Wolpert and Wolpert (1976) present a general discussion of the policy of returning to the community long-term patients who do not require the full range of hospital services. The authors also discuss reducing the duration of stay for newly admitted patients and preventing hospital admission of clients who could be served in the community. They examine the impact of this policy on the mental health system, the community, and the criminal justice system, and they note the lack of suitable after-care programs and the tendency of many patients released from hospitals to be relocated in the inner city ghettos.

To evaluate this process, they formulate a generalized assignment model. The model, which is developed only conceptually, uses the number of favorable treatment outcomes as its objective function. Such a model requires data that are not widely available, such as information on the precise determination of outcome by defined classes of treatment methods. However, the authors argue that such a model is a good heuristic devise for defining information needs of high priority and also for providing a formal structure for the analysis of the effect of deinstitutionalization.

Correa and Sangl (1977) review several mathematical programing models for drug abuse control. First, they discuss several rather simple aggregated models usually based on linear programing. These models have been used to evaluate a small number of policy alternatives in the treatment and control of drug abuse. The authors then present a disaggregated linear programing model--with treatments spanning from alcohol and drug abuse to criminal justice, mental health, the community, and also general health care. In this model, they consider two age groups, those under 30 and those 30 and above. Another good indicator of the detail of the model is found by examining the nine treatment possibilities: detoxification, civil commitment, therapeutic communities, outpatient abstinence, antagonist treatment, minimum and maximum methadone maintenance, heroin maintenance, and prescription heroin.

The study is noteworthy in that it reviews the literature to provide estimates of key parameters for a number of sample runs of the model. The examples include examination of the effects of changes in the financial resources available for the control of drug abuse, and the effects of changes in the solutions when the constraints for employment, crime, and alcohol abuse are modified. The authors emphasize that their conclusions should be interpreted with great caution because of the unreliability of their data, the simplicity of the examples they investigate, and the lack of sufficient simulation runs with their models.

Their study is important in several respects, nevertheless. First, it goes beyond a linear programing model to examine more realistic dynamic programing and probabilistic models. Second, it demonstrates how available literature in the field of drug abuse can be used to provide the necessary parameters for the models. Analysts should use special care in interpreting the results obtained from models when unreliable data are used and should be wary of the false sense of security that a model provides. The lack of reliable data is not necessarily an obstacle, however, to the mathematical modeling approach. The model provides at least a structured framework for analysis. As more data become available, such optimization models will take on even greater importance.

A third way of dealing with large-scale system interactions would be to combine simulation and optimization techniques in one model. Kropp et al. (1979) describe the application of such a combined model in ambulatory health care. Such a method uses an optimization technique to analyze the system at an aggregate level. The results are then used in a simulation model of the same system to identify other information that can be passed back to the optimization model. The reason for employing both an optimization model and a simulation model is that optimization methods can answer most questions asked by the analyst, whereas simulation models cannot. Because simulation is descriptive, it can answer questions concerning little more than the feasibility of a given alternative unless the analyst uses a complete experimental design.

A combination model permits the analyst to use the optimization model to reduce the number of variables and the resultant number of alternatives to be examined by simulation. The simulation model is then used to handle the system's complex relationships (such as nonlinearities, queueing, and discreteness), which are too cumbersome for the optimization model. Thus, the "recursive" method attempts to capitalize on the advantages of both approaches while attempting to reduce the disadvantages of either method used by itself.

Although it is too early to identify the actual benefits of using such a combined technique, the technique itself is intuitively appealing. In particular, researchers perceive the need in many cases to link the results of simulation trials with resource allocation methods so that program design can be dealt with on the basis of cost optimization subject to constraints. The combined technique attempts to meet such needs.

The three basic modeling techniques--optimization, simulation, and optimization simulation--appear to be useful in many situations, but actual implementation of the methods can prove quite difficult for several reasons.

First, it may not be possible to build quantitative models that reflect accurately the operation of the various systems. In many cases, the important descriptions of the systems involve subjective considerations that may not be quantifiable.

Second, the assumptions of the models may be unrealistic. For example, optimization models work only when the decisionmakers have identified objectives as well as constraints. If the objectives and constraints are not known, then only simulation models may be appropriate. Even then, simulation models will be useful only if they are realistic and are capable of providing information about the measures of performance that are of interest to decisionmakers. The same points also apply to the cases in which the optimization-simulation methodology is attractive.

Finally, the data requirements of the models may be so great as to preclude implementation. Attempts to use realistic optimization, simulation, or optimization-simulation models appear to have had limited success in many cases, because sufficient data were not available. In such instances, the modelers have been placed in the precarious positions of modifying the models or of guessing at the values of the missing data. In either case, the models have lost at least part of their explanatory power.

In summary, operations research methodologies have the potential of aiding decisionmakers and helping them gain an improved understanding of the operation of the mental health service system and its interactions with other systems. There are many problems, however, that will continue to make it difficult for researchers and model users to realize this potential.

V. RECOMMENDED RESEARCH UNDERTAKINGS

Section IV discussed generally how operations research methods could be useful in dealing with large-scale systems interactions. Specifically, it identified three modeling methods that have been used and should continue to be useful in the future. These modeling methods are systems dynamics, optimization methods (especially linear programing), and the combined optimization-simulation method. This section identifies specific applications of these methods that warrant immediate research attention.

Before examining these specific applications of operations research methodologies in mental health, it is important to emphasize the perspective from which such efforts must be seen. Specifically, the operations research methodologies must be viewed only as an aid to decisionmakers who have to deal with major policy questions. To highlight this point, it is convenient to use a matrix, such as that depicted in table 4. An individual or group considering use of operations research should enter the matrix from the left--that is, by taking a problem- or question-oriented approach. The questions depicted here are those mentioned in section II. Obviously, this list is only an example; it is not all-inclusive.

Table 4. Research areas and major policy questions

MAJOR POLICY QUESTIONS	RESEARCH AREAS				
	Data collection within delivery systems	Data collection of at-risk population	Simulation models	Optimization models	Simulation-optimization models
Deinstitutionalization					
Primary care/ mental health care interactions					
Variations in per capita use of care for mental health problems					

Section IV argued that it was not appropriate to attempt to fill out the large-scale systems dynamics model of section III. It may be appropriate, however, to attempt to construct a less-detailed, general macromodel describing the flows within the system and crudely depicting externalities. If constructed carefully, such a model could be used at various levels of specificity to determine data needs and accuracy and to pinpoint sensitive areas requiring more microscopic modeling.

The first specific research area involves data collection and organization. Obviously, this does not involve specific operations research methodologies. Because collection and organization of data are critical to the use of these methodologies, however, the importance of this research area cannot be overemphasized. Some reference to the data requirements of operations research methods has been made previously, especially by Kramer (1977). However, Kramer is concerned with information about the distribution of mental disorders and the patterns of use of mental health services. Such information is targeted toward and is useful in the operation of community mental health centers and other mental health agencies. These areas are important, but there is also a compelling need to develop decisionmaking data of the type needed for the applications of operations research methodologies.

The Correa and Sangl (1977) article is exemplary in that it demonstrates the potential of operations research as an aid in decisionmaking. It is necessary to note, however, that reliable data were not available to Correa and Sangl. They had to perform extensive literature reviews and analyses to provide the following information for their linear programing model: success and failure rates of various treatment modalities; employment rates; crime rates; other drug abuse rates; and treatment costs. Such data might already have been developed; however, if the data are available, they are so widely scattered as to be of little use. Therefore, there is a great need to start collecting, organizing, and consolidating these data if we are to make any significant progress in the use of operations research methods.

A great deal of the information that has already been collected concentrates only on one system and, as a result, is of little value in trying to deal with interactions between systems. What is needed are data that track individuals as they move from one system to another. Such information should be specific to patients, not systems. As Dr. Christopher Dunn of NIMH mentioned at the NIMH operations research conference, the types of data needed on patient flow and contact are much more available in some European countries. Individuals considering this research area may well want to examine the experience of such countries.

A second research area involves further examination of the previously mentioned changes in composition of the populations for outpatient and inpatient mental health services and examination of the implications of those population changes. Systems dynamics models could be a useful methodology in this area. In particular, the models would permit the investigator to examine the total problem rather than force him or her to analyze each area independently and then to infer the results. Using such a methodology, an analyst could perform many simulation runs to examine the effects of various policies, such as the continued support of community mental health centers.

A third research area involves further examination of the placement of deinstitutionalized patients in the community and in nursing homes. There is a growing consensus that, although some objectives of the deinstitutionalization effort have been realized, much remains to be done. In many locations, for example, the rate of use of State hospital facilities has declined dramatically. The rate of readmission of patients to State hospitals, however, has often remained the same or has actually increased. The combined optimization-simulation methodology could prove very useful in identifying how to do a better job of placing the deinstitutionalized patients. Given goals (such as maximizing census reduction in State hospitals) and constraints (such as the amount of money available), the optimization model in such an analysis could allocate patients to the various programs. The simulation model then could evaluate the effects of these allocations, given specified outcome probabilities. Using this methodology, an analyst could follow the Correa and Sangl approach of determining attractive policies by performing different optimization runs with varying resource limitations.

A fourth area in which more extensive research is needed is the interface between the mental health service system and the general health system. The Correa and Sangl optimization approach could be very useful in this area. In particular, it could examine the various alternatives, such as (1) freestanding outpatient medical clinics, (2) psychiatric units of general hospitals, (3) training programs to increase the capabilities of primary care physicians, and (4) increased availability of social service agencies.

A fifth research area involves identifying the potential implications of a shift of the mental health diagnosis and treatment functions to the general health sector. Patients with identified mental disorders seem to be using general medical services at a rate at least double that of other patients (Regier et al. 1978). If this is true, we need to understand the implications of this increased use of primary health care because of the resulting increase in the number of mental diagnoses and because of possible national health insurance programs. The systems dynamics methodology could be helpful in examining this area. In particular, there is a strong feedback loop from the general health care sector to the mental health sector and then back to the general sector.

The recent literature review and critique by Jones and Vischi (1979) makes a significant contribution in this area of overlap between mental health care and general health care. The study indicates that a reduction in medical care utilization does appear to occur after treatments for alcohol and drug abuse and mental disorder. Although the study points out the need for more research, we have at least some information about the patient flows from the mental health care system to the general health care system. What remains to be examined is the other important flow--that from the general health care system to the mental health care system.

There is also need to examine the effects of various financing mechanisms that seem to be encouraging this shift. In particular, the current direction of financing efforts is (1) to provide mental health service coverage for more and more people, and (2) to provide more for generalized outpatient care than for specialized inpatient care. The federally assisted community mental health centers are good examples of the results of such financing efforts. Thus, it is imperative to understand the impact of such efforts on the resource needs in general health care. This shift of patients and resources toward the general health care system could lead to overuse of general facilities and underuse of the specialty mental health facilities. Although systems dynamics may be helpful in examining the patient flows, the optimization techniques could be equally useful in examining the resource allocation problems.

The last area of research need does not involve operations research methods themselves. It concerns the behavioral, communications, and organizational structures critical to the implementation of the results of operations research studies. Health operations researchers believe increasingly that the development of rigorous models has been stressed at the expense of effective implementation of models. This being the case, there is a need to focus increasingly on implementation in addition to the modeling efforts.

Pondy (1975) describes three ways in which the behavioral sciences can contribute to improving health operations research: (1) by providing a perspective on the relationship between the analyst and the health systems; (2) by providing insight into human factors within the health system; and (3) by shedding light on the general problem of redesigning social systems and the role operations research can play in that process of redesign. The behavioral sciences will also be useful in helping to identify providers' and consumers' expectations about their new roles and the relevant roles of others in the systems.

VI. CONCLUSIONS

Review of the available literature and examination of currently used planning practices indicate that little effort has been expended to model the large-scale interactions between mental health care systems and other systems. There are several reasons for this lack of effort. First, as is evidenced by the discussion in section III, the task of modeling as complex a system as that of mental health care is extremely difficult. Second, as noted in section IV, the data required in such a modeling effort are scarce. In spite of these difficulties, recent trends in U.S. health care, such as those identified in section II, emphasize the importance of examining the large-scale system interactions.

To understand even better the importance of these interactions, one needs only to read recent legislation concerning health care. In many cases, authorizations for new programs stress that the money is for coordination for existing services and not for additional doctors, nurses, or equipment. Such ideas indicate that coordination of the elements of the system is a key to cost-containment and improved service. These coordination efforts cannot proceed without an understanding of the large-scale system interactions.

Operations research methodologies definitely can be helpful in efforts to examine these interactions. It is important to recognize, however, that our ability to understand these interactions and to consider their implications in planning does not depend only on operations research techniques. Two equally important areas are collection and organization of the data needed by operations research models and behavioral considerations useful in dealing with implementation issues. As a result, expanded research in these areas must be encouraged.

Because these latter two areas have also been neglected and because resources are limited, it is not advisable now to proceed in the direction of building a large systems dynamics model similar to that discussed in section III. A more useful approach might be to use the tools of operations research to study smaller problems--those with only a few important system interactions. Such an approach would improve our understanding of the detailed operation of the mental health system and thus put us in a position to examine large-scale problems in the future.

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